Emerging Technology Zero Emission Vehicle Household Travel and Refueling Behavior

(CARB Contract 16RD009)

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Abstract

Results from this report highlight how alternative fuel vehicles are used based on data collected between 2015 and 2020. Alternative fuel vehicles include plug-in electric vehicles (PEVs), vehicles that are either battery electric vehicles (BEVs) or plug-in hybrid electric vehicles (PHEVs), and fuel cell vehicles (FCVs). This category of vehicle technologies is included in the California Air Resources Board's Zero Emission Vehicle regulations and is referred to as ZEV in this report. We explore the environmental impacts of driving, charging behavior and infrastructure. In households with ZEVs, the data from surveys, loggers, and interviews indicate that those vehicles are being used extensively. This report, which combined the data collected in two consecutive studies between 2015-2020, includes first and second generation PEVs popular in California between 2011-2018. The BEVs include the first-generation, short-range Nissan Leaf and the long range BEVs such as the Chevrolet Bolt and Tesla Model S. The PHEVs include short range sedans such as the Toyota Prius Plug-in and longer-range vehicles such as the Toyota Prius Prime, Chevrolet Volt and Chrysler Pacifica. The FCVs include the most popular fuel cell vehicle, the Toyota Mirai.

In replacing household gasoline miles with electric miles, the results of this study suggest a significant difference of this driving behavior according to vehicle range and battery size. While we cannot say that this driving behavior is directly influenced by vehicle characteristics such as range, size, and performance, we can, however, observe the trends in driving behavior of participants who own the same vehicles. For example, it is important to note that longer-range PHEV users in this study had the tendency to plug in their vehicle more and achieve higher electric vehicle miles traveled (eVMT). It is also plausible that similarities in driving behavior between users who own similar vehicles are coincidental, since infrastructure availability and other variables aside from vehicle characteristics could be the main variables in vehicle performance.

Overall, the results suggest, as expected, that longer-range PEVs have more electrified miles than those of shorter range PEVs. However, to maximize the impact of PEVs, a full set of policies is needed to address charging behavior and vehicle purchase. FCVs in our sample are being used for long commutes, but not on long road trips, based on local refueling infrastructure deployment. The results in this report point to factors that affect the environmental impact of ZEVs, including charging behavior, household fleet composition, vehicle usage, and more. Further research is necessary to shape policies that lead to more sustainable transportation and ZEV usage. The household analysis suggests that longer-range ZEVs can reduce the environmental impact of transportation, however future households may move to two ZEVs; combining BEVs or FCVs with PHEVs, or short-range BEVs with long-range BEVs, which would significantly increase the electrification of miles at the household level. The report's main limitation is the sample size of logged households.

Preface

The purpose of this report is to understand, under real world conditions, the emission potential of zero emission vehicles (ZEVs), as defined by CARB regulation, to highlight benefits and challenges, and to present needs for improving and regulating future vehicles. This report includes data from three distinct zero emission vehicle types; plug-in electric vehicles (PEVs), which includes both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), and fuel cell vehicles (FCVs). This report covers data collected from the original Advanced Plug-in Electric Vehicle Travel and Charging Behavior report (CARB

Contract 12-319[1]) and updates it with data collected from additional models between 2018-2020 and a new section on fuel cell vehicles (CARB Contract 16RD009). We also updated the cold-start section that was part of the original report. This Emerging Technology Zero Emission Vehicle Household Travel and Refueling Behavior report allows us to monitor how new PEVs are being used on a day-to-day and month-to-month basis within a household travel context, by placing data monitoring devices (loggers) in all vehicles in participant households for a period of one year. The combined projects provide a common basis to evaluate technologies comparatively and in a consistent way. The data was collected from all the vehicles in the households, including ICEVs and the ones in the original report, with a focus on the larger group of two vehicle households. The report includes the five years of data collection from different vehicles that have no standardized protocol for data reporting. Over these five years, loggers were installed on about 800 vehicles, including ZEVs and ICEVs. The result is the collection of 7 million miles of data, including 4.3 million miles that were collected from alternative fuel vehicles.

The main additions to this report are: (1) updating the sample size of the original report to get a better representation of vehicle usage in California, (2) updating the household level analysis by adding a larger sample of two and three vehicle households, (3) adding battery electric vehicles with longer ranges, lower priced BEVs, and larger platform PHEVs such as the Chrysler Pacifica minivan, (4) adding fuel cell vehicle analysis, (5) updating the engine cold-start analysis for plug-in hybrids, and (6) conducting a new set of interviews.

Acknowledgements

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[1] https://ww2.arb.ca.gov/sites/default/files/2020-06/12-319.pdf

Executive Summary

This Emerging Technology Zero Emission Vehicle Household Travel and Refueling Behavior Report monitors how new plug-in electric vehicles (PEVs) and fuel cell vehicles (FCVs) are being used on a day-to-day and month-to-month basis within a household travel context. This was done by surveying owners and placing data monitoring devices in all vehicles in participant households for approximately one year, including conventional or non-plug-in hybrid internal combustion engine vehicles (ICEVs). Over five years of data collection, loggers were installed on about 800 vehicles, ZEVs and ICEVs alike, that had no standardized protocol for on-board data reporting. The result is the collection of 7 million miles of data, including 4.3 million miles that were collected from alternative fuel vehicles. The first project began with studying several models of plug-in vehicles. PHEVs included the following: (1) the Toyota Prius Plug-in (Model Years [MY] 2012–2016), (2) the first-generation Chevrolet Volt (MY 2010–2015), (3) the Ford C-Max Energi PHEV (MY 2014-2016), (4) the Ford Fusion Energi PHEV (MY 2014-2016), and (5) the second generation Volt (MY 2016). The BEVs included the following: (1) the first generation Nissan Leaf (MY 2010–2016), (2) the second generation Leaf with a 30kWh pack (MY 2014–2016), (3) the Tesla Model S with battery size of 60-100kwh (MY 2013-2017), and (4) the Toyota RAV4 EV with battery size of 41.8kwh (MY 2012-2014). Over time, the project expanded to include new additions to the market, including the Prius Prime-8.8, the Pacifica-16, the Bolt-66, and the Toyota Mirai FCV.

The data collected shows that longer-range BEVs and PHEVs, vehicles with larger batteries, had a greater substitution of gasoline miles with electric miles. The same results are true for both vehicle level and household level analyses. While exploring vehicle usage, we learn that short range BEVs were not used for long road trips or long freeway speed trips. As battery price drops and driver preferences and needs are clearer, the future supply is not anticipated to include BEVs with a range lower than 100 miles. The analysis found significant differences between the use of the longer-range BEVs and that of shorter-range vehicles. In addition, there were notable differences between long-range BEVs, the Bolt-60 and the Tesla Model S, in our study. The Bolt-60, for example, recorded 6.8% of miles with speeds higher than 75 mph whereas the Tesla sample population logged more than 12% of their miles as high-speed miles. Tesla drivers also used DC fast charging further away from home than other BEVs, which illustrates another difference in usage between long-range BEVs.

Our survey shows that there is a greater share of alternative vehicles used for commuting in comparison to the California fleet. On average, the BEVs in our study charge less than once a day, including days when the vehicle was not used as expected. DC fast charging is still used mostly around home, within a radius of less than half the vehicle range from their home location. Only Tesla vehicles use DC fast charging for longer trips in a substantial way. Level 1 charging was also significant for all vehicles' long, overnight trips. All the FCVs in our sample were used for commuting, similar to short range BEVs, and other small vehicles in our sample and were not used for long road trips. In households with two vehicles, the FCV accounted for 50%-70% of the total household annual miles.

While most modeling and early assumptions hypothesized that electric vehicle drivers would plug-in every night and start each day with a full battery, our results show that charging every other night is more common for longer range BEVs or when driving less, while charging more than once a day is common for PHEVs who drive more than their electric mileage range. The interviews that were conducted show the importance of charging policy and charging management in the workplace, which can inform the optimization of charging infrastructure. The interviews explore what could cause a low frequency of workplace charging such as charger congestion, convenience, and dependability.

We had a small sample of Toyota Mirai FCVs in our study that were used for an average of 10,700 miles per year including long commute days, but a small number of long road trips. In households with two vehicles, the FCVs account for 50%-70% of the VMT.

For PHEVs, our study presents lower utility factor (share of electric miles driven over total miles driven) values than those of the EPA (Environmental Protection Agency) results, primarily from driving more than the expected mileage used for estimating the utility factor, but also from driving at higher speeds than simulated. We also learned that PHEV drivers with larger batteries charge their vehicles more when needed, achieve higher utility factors, and have many days with no engine starts at all, compared to PHEV drivers with smaller batteries.

Overall, the results indicate that longer-range PEVs have more electrified miles than their shorter-range counterparts, resulting in a reduced greenhouse gas (GHG) footprint. The results of this study address possible factors that affect the environmental impact of ZEVs. This study focuses on ZEV performance and household performance but did not collect data to compare those households to the general population and ICEV-only households. This nature of the data collected for this study introduces two key limitations: first, no data was collected on ICEV-only households, which limits our ability to extrapolate from these results to the general population or new-car-buying households; second, the data collection for this study spans 5 years and may include behavioral changes in society as a whole or among ZEV drivers. To maximize the benefits of PEVs, a full set of policies is needed to address charging behaviors and vehicle purchases. As those factors continue to change over time, ongoing research is necessary to better shape the policies that lead to more sustainable transportation and efficient ZEV usage.

1 Introduction

Road transportation accounted for 21% of global energy consumption (Contestabile, Alajaji et al. 2017) and it will increase unless the share of carbon intensive transportation fuels is substituted by cleaner sources. Plug-in electric vehicles (PEVs), which include full battery electric vehicles (BEVs) as well as plug-in hybrid electric vehicles (PHEVs), and hydrogen fuel cell vehicles (FCVs) are promising alternatives to conventional internal combustion engine vehicles (ICEVs) because of their energy conversion efficiency and reduced tail-pipe emissions. Over 1.5 million electric vehicles have been sold in the United States, and over half of those were sold in California. Nevertheless, gasoline-powered vehicles and other conventional-fuel vehicles still constitute 98% of the light duty vehicle (LDV) fleet (**Figure 1**). For this report, conventional vehicle powertrains such as gasoline, gasoline-hybrid (HEV), flex-fuel, diesel, and diesel hybrid vehicles will all be included under the umbrella term of ICEVs, since they are not the focus of this report.

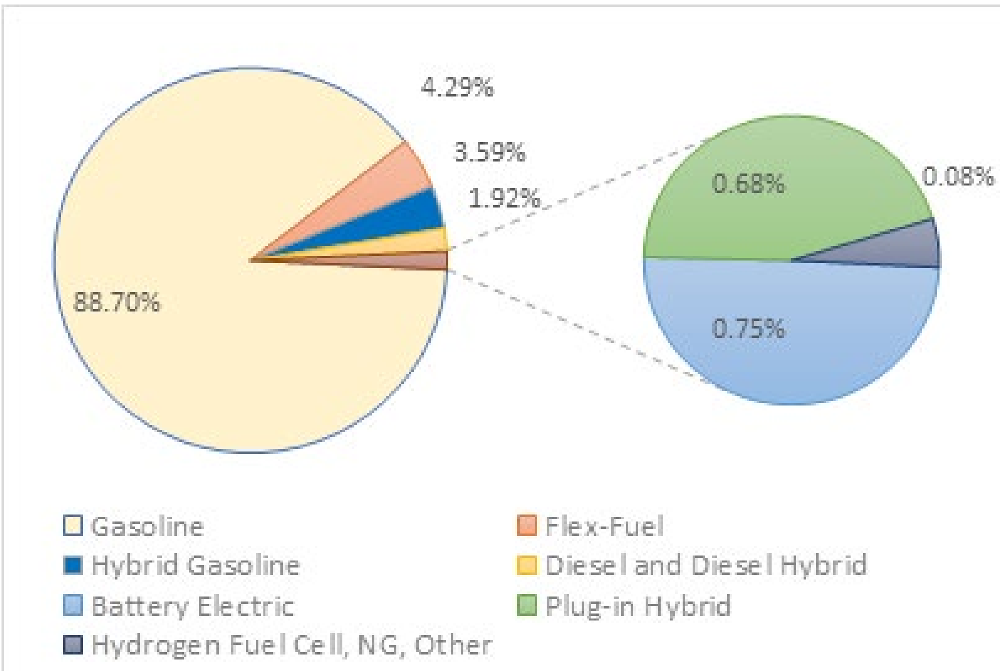


Figure 1. California LDV Fleet Composition (2018) by Fuel Type (CA Department of Motor Vehicles, published 2019)

The market share of BEVs and PHEVs has been increasing over the past decade. The share of hydrogen fuel cell vehicles (FCVs) has been considerably lower than the share of BEVs and PHEVs as illustrated in **Figure 1**. According to the California DMV and data reported by the California New Car Dealers Association, the share of PEVs in total new vehicle sales/registration went up from 3% in 2014 to 8% in 2019 (**Figure 2**). In addition, the share of PEVs in the total LDV stock of California increased from 0.4% in 2014 to 1.43% in 2018.

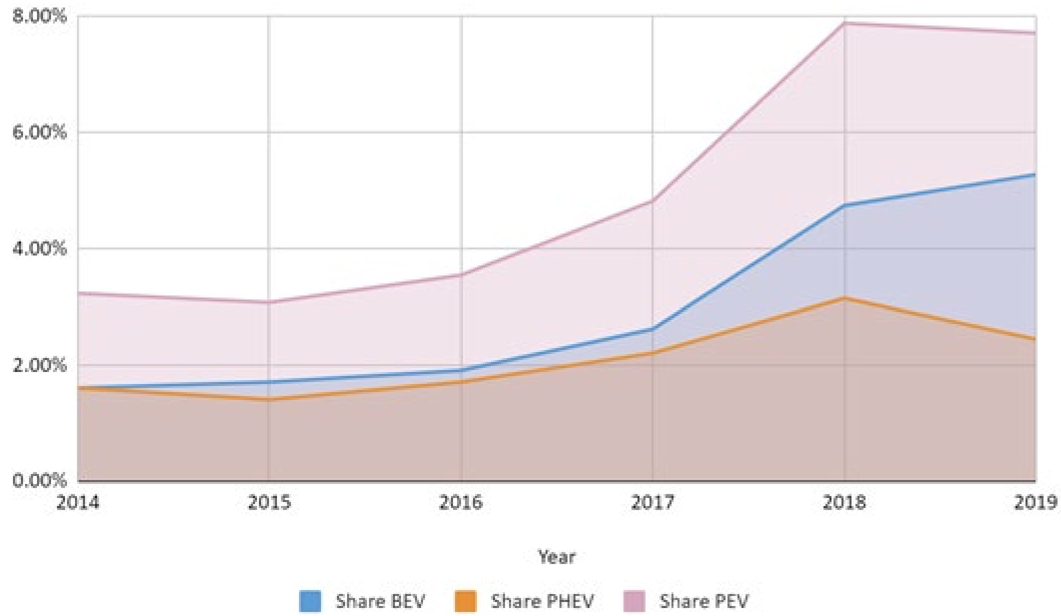


Figure 2. Share of BEVs and PHEVs in New Vehicle Registration (Source: California New Car Dealers Association)

The deployment of vehicles so far is not evenly distributed; areas with higher income population and more total vehicles have a higher share of electric vehicles. (**Figure 3**)

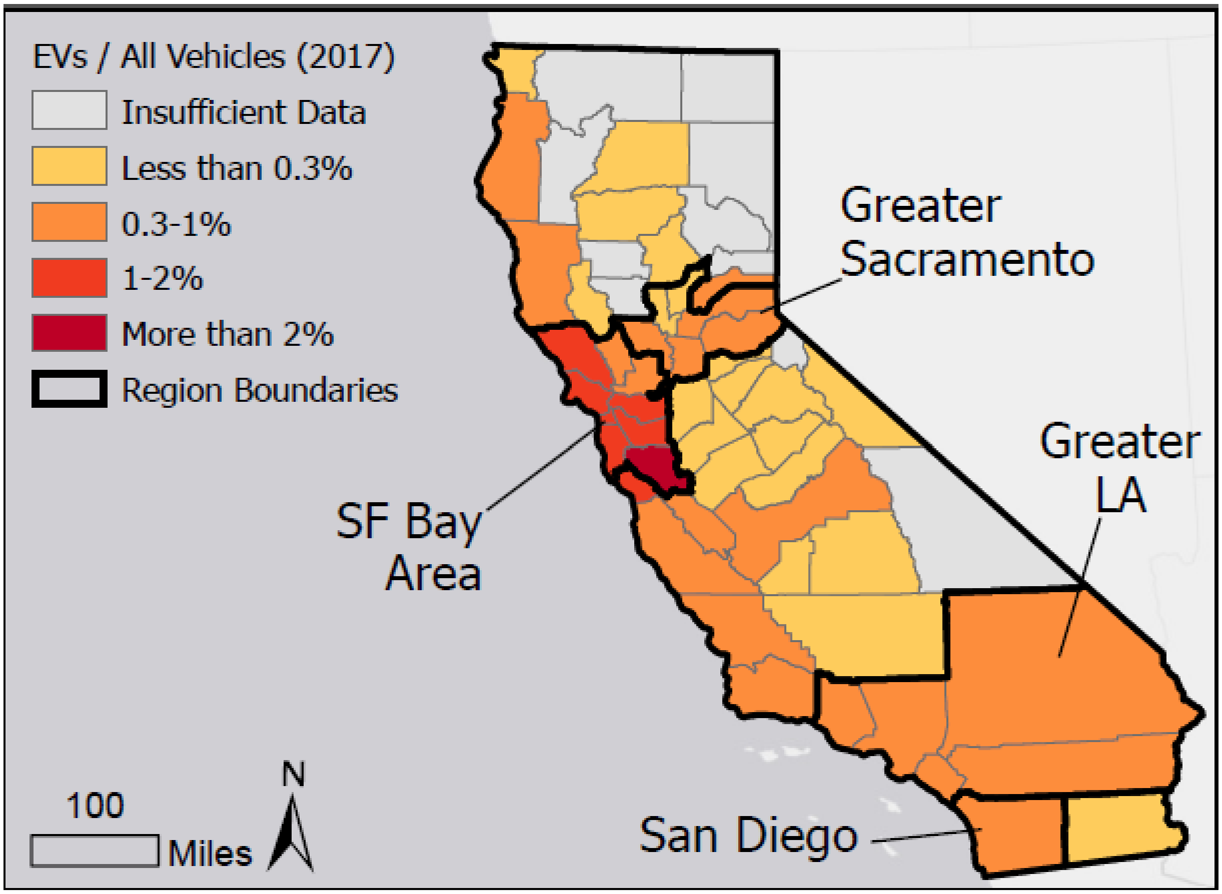


Figure 3. PEVs as share of all vehicles

When it comes to BEVs, a large share of the rebates in the past couple of years have gone to Tesla buyers while the share of Nissan Leaf rebates has dropped among first-time BEV adopters. In the case of PHEVs, adopters of the Chevrolet Volt, Toyota Prius Prime, and the PHEVs offered by Ford, like the Fusion and the C-Max Energi, have claimed the majority of CVRP (California Vehicle Rebate Project) rebates. These trends in CVRP application data based on vehicle make reveal the composition of the PEV fleet in California in terms of vehicle characteristics such as electric range and battery technology.

PEV usage, including charging and driving behavior have a major impact on the energy and environmental benefits of these vehicles. There are many variables that discourage the adoption of PEVs, including limited electric driving range, household access to charging locations with various capabilities, costs, and charger access rights as well as behavioral variables, such as the habits and desires of households for using these new types of vehicles. PHEVs may charge more or less frequently, resulting in a higher or lower percentage of electric powered VMT (eVMT)—where the proper denominator for calculating the percentage is the household's total VMT, not merely the total VMT of the PHEV. Such complexities can complicate attempts to predict and calculate the impact of recent technologies on emissions in the coming decades. This study identifies and begins to measure these new patterns.

Consumer's perceptions on PEVs' ability in meeting daily mobility needs compared to ICEVs, higher upfront capital cost compared to ICEVs, range anxiety, and reliable access to charging infrastructure continue to be major barriers to large-scale PEV adoption (Dimitropoulos, Rietveld et al. 2013, Liao, Molin et al. 2017, Lutsey, Meszler et al. 2017, Hardman, Jenn et al. 2018). These barriers create uncertainties in the evolution of the PEV market. Heterogeneities in daily driving patterns and needs across various sociodemographic indicators and geographical locations, further compound these uncertainties. Since PEVs are uniquely positioned to interact with the energy and the transportation sector, uncertainties in the evolution of the PEV market pose many problems for policy makers, auto manufacturers, electric utility companies, and charging infrastructure developers (Wietschel, Plötz et al. 2013). Policy makers have to continually fine tune existing incentives (financial and/or non-financial) or introduce new incentives to encourage the adoption of PEVs. Understanding daily driving needs is crucial for auto manufactures for optimal PEV design and model choice offerings. Charging infrastructure developers have to ensure that electric vehicle supply equipment (EVSE) is efficiently located and managed to alleviate concerns about range anxiety and accessibility to EVSE. Utility companies are particularly concerned about PEV charging patterns as it has the potential to create localized hot spots when not managed properly, necessitating network upgrade or expansion (Muratori 2018). Utility companies also would have to design their PEV specific rates keeping in mind when and where PEVs are charged.

The decision to own a PEV or FCV will have long-term consequences on the user from a total cost of ownership (TCO), value proposition, and life-time GHG reduction potential perspective. The user's daily driving and charging behavior will have short-term impacts on planning charging infrastructure roll out and effectively managing the incremental demand imposed by PEV charging. To better understand the impacts of PEVs across varying timescales given their negligible global share and the scarcity of their usage data compared to ICEVs, studies have relied on existing data to model their behavior. Modeling PEV driving behavior will offer qualitative and quantitative insights into the feasibility of PEVs in replacing a conventional vehicle. The daily and long-term energy, emissions, and economics of PEVs/FCVs are related to the extent in which prospective and current PEV/FCV owners perceive the daily driving utility of these vehicles when compared to a conventional vehicle. The charging demand imposed specifically by PEVs is affected by their daily driving distance and dependent on their trip start times, end times, and dwelling times.

Given the relative scarcity of actual ZEV usage data, researchers and policymakers create scenarios by combining various sources of travel data and superimposing a set of preconceived expectations about ZEV driving and charging/refueling needs. There has been an increase in efforts to analyze data from the real-world operation of PEVs to estimate eVMT, since it is the most widely adopted metric to determine the potential of electricity as a transportation fuel. The scope of such efforts has expanded recently to estimate the zero emission VMT, or zVMT, which is the miles traveled on electricity only. For BEVs and FCVs, VMT, eVMT, and zVMT are the same. However, for the PHEVs, due to their dual modes of operation, zVMT is lower than eVMT. Information about ZEV usage based either on assumptions or from real-world operations have direct consequences on not only their VMT, eVMT, zVMT energy consumption (electricity, hydrogen, and gasoline) and emissions (from driving and charging), but also on specific policies that rely on them, such as credit allocation under the ZEV mandate (CARB 2017) and PEV infrastructure projections and investments (Wood, Rames et al. 2018, Brecht and Orenberg 2019).

There are many variables that are presumed to interfere with the assumption of a ZEV for a previous conventionally fueled vehicle, including limited electric driving range, household access to charging/refueling locations with various capabilities, costs, and charger access rights as well as behavioral variables such as the habits and desires of households for using these new types of vehicles. Depending on travel needs, desires, fuel costs, charging opportunities, and how much drivers like or dislike their ZEV, they may end up using their new ZEV for more or less vehicle miles traveled (VMT) than they had for a previous vehicle. With PHEVs, they may charge more or less frequently, resulting in a higher or lower percentage of electric powered VMT (eVMT)—where the proper denominator for calculating the percentage is the household's total VMT, not merely the total VMT of the PHEV. This report identifies and begins to measure these new patterns.

FCVs have even lower adoption rates than PEVs despite having high driving ranges, with the Toyota Mirai surpassing 300 miles of range and refueling times equivalent to that of ICEVs. The main barriers impeding the adoption of FCVs include scarcity of hydrogen infrastructure, relatively high purchase price, inability to refuel at home and safety concerns (Hardman, Shiu, Steinberger-Wilckens, & Turrentine, 2017). In California, there are 41 active hydrogen fueling stations that are mostly concentrated in and around dense metropolitan areas such as Los Angeles and San Francisco. The sparse and selective spatial distribution of refueling stations can serve to discourage potential adopters from purchasing FCVs due to refueling inconvenience. The high purchase price owed to the high cost of fuel cells and hydrogen tanks coupled with the lack of economies of scale also drives potential buyers away from FCVs (Hardman et al., 2017). The strategic, concurrent adoption of FCVs and PEVs can reduce a significant proportion of transportation related carbon emissions. Despite FCVs having lower well to wheel efficiencies than many PEVs, their usage can still have positive environmental benefits from an emissions perspective if they are specifically adopted in regions where the electricity grid is largely coal based (Hardman et al., 2017). As it is for PEVs, there is little empirical research on FCV usage. This study analyzes vehicle usage data collected from a small number of households with Toyota Mirai to uncover usage patterns that can potentially be indicative of FCV impacts on carbon emissions in the coming decades.

Travel behavior researchers have known that the household is the critical unit to study because activities are often allocated among a fleet of household vehicles on a trip-by-trip basis. Previous studies of household vehicle travel have been for short periods or have not used data loggers. However, this project studied the use of vehicles by the household, instrumenting all their vehicles with GPS enabled logging devices, to accurately measure the trip allocation and activity route formation of the whole household across a year.

This research is designed to investigate these household travel patterns and lifestyle activity spaces in response to PEVs/FCVs across a large set of households.

The overarching objective of this research project is to collect and analyze longitudinal, spatial, and in-use vehicle data, including eVMT, from a variety of plug-in electric vehicles (PEV models). PEVs are imperative in achieving California's long-term air quality and climate stabilization goals. This means measuring the travel and fueling of all vehicles within a PEV-owning household is important. Usage and charging habits of PEV owners remain ambiguous due to the diversity of PEV designs, technologies, electric ranges, and the failure to account for other travel within households. However, these behaviors will have significant implications for statewide emissions, energy consumption, and electrical grid management based on the miles these vehicles travel using off-board electricity sources. The secondary objective of this project is to collect and analyze in-use vehicle data from FCVs, specifically the Toyota Mirais. FCVs can also serve to further California's air quality goals, especially when used in regions with high-carbon electricity grids. Objectives include:

1. Determining the share of PEV miles traveled, powered exclusively by off-board electricity (eVMT), and how emissions profiles might differ between the several types of PEVs.

2. Learning the allocation patterns between household vehicles for daily, weekly, seasonal, and infrequent trips. Knowing these reasons will assist CARB and others in creating policies to increase eVMT in the future and better estimate current eVMT.

3. Learning recharging patterns of PEVs in a household context. These patterns can assist CARB and other State partners in developing the charging network in ways that might help households maximize their eVMT. Additionally, knowing the locations and times of charging events could help CARB and partners to assess the time-of-day emissions impacts, and perhaps influence the recharging of PEVs in a way to reduce emissions and optimize the use of the grid across time and seasons. The same data can also assist utilities and their regulators to understand grid impacts from PEV charging, rate impacts on charging behavior, and the need for public infrastructure. Temporal and spatial data would provide a better picture of when and where PEVs are charging, which informs upstream emissions estimates.

4. Understanding how any measure of eVMT develops within the overall travel of households because of systematic variation caused by, for example, household self-selection of different types of PEVs. Furthermore, while an individual PEV may have a high share of eVMT, total transportation-related emissions from the household, it will also depend on the activity and usage of all other vehicles in the household fleet, as well as other modes of transportation used, such as public transportation.

5. Characterizing the engine start activity profiles of blended PHEVs. In the 2017 market, many PHEVs are "blended" in the sense that an internal combustion engine (ICE) can start to help power the vehicle before the battery is depleted. These ICE starts occur when the electric drivetrain is not sufficient to meet immediate high torque demand, regardless of the battery state of charge. These ICE starts occur under high power demand scenarios and are distinct from cold starts for conventional vehicles, which typically occur with the vehicle stopped, in park/neutral, and with a low immediate torque demand. PHEVs likely have a different distribution of engine-on events compared to conventional vehicles and these can occur due to battery depletion as well as high-torque demand events. The results of this study can be used to improve the emission inventory model (EMFAC) in estimating PHEV start emissions. The results can also be used to guide the development of future clean car standards.

6. Studying the driving and refueling behavior of FCV vehicles. This includes understanding the allocation patterns between household vehicles for daily, weekly, seasonal, and infrequent trips. It also involves determining the location of and duration between refueling events. The metrics from these analyses can help CARB and other state partners determine optimal locations for hydrogen fueling stations in order to promote the adoption of these environmentally clean vehicles.

2 Recruitment and Background Survey

This report seeks to collect the data that can answer essential questions about future travel and charging behavior and refueling of ZEV owners in California households and the benefits that are likely to result. What are the environmental benefits of these vehicles? How much travel can and will be shifted to PEVs, and specifically to BEVs and to PHEVs, per vehicle and for the household fleet? What kind of charging network is needed?

The funds for this project cover collection, cleaning, and basic analysis of the data, but not the analysis aimed at understanding the interaction between the data factors collected and potential correlations. This study uses data from three main sources: 1) survey data of PEV households, 2) vehicle-level data collected from 303 households through loggers connected to the vehicle telematic system, and 3) interviews of 40 PEV users that participated in the logging component. This research helps identify ways to facilitate increased use of zero-emission vehicles (ZEVs) by Californians. Also, longitudinal, temporal, and spatial data provide a picture of when and where PEVs are charging, as well as the electric- and gasoline-vehicle miles traveled by PEVs and other vehicles in the household.

A detailed, 30-minute recruitment survey of ZEV owners/lessees (hereafter referred to as owners for simplicity) was conducted to determine how many participants would be needed for each region and sociodemographic group so that the results would be representative of statewide ZEV owning households—i.e., so the results could be generalized to the wider population. The survey included eight categories of questions: travel behavior, driving behavior, vehicle performance (MPG), vehicle characteristics, response to ZEV related incentives, vehicle purchase history, current household vehicle fleet, sociodemographic characteristics, PEV charging behavior and FCV refueling behavior. The survey targeted owners of all ZEV models in the market at the time of the survey. The initial survey also was the first step in recruitment, asking whether respondents would be willing to participate in the second part of the study by having a logger installed in their vehicle. The information also helped determine whether household vehicles were suitable for participation based on logger limitations and vehicle usage (appropriate mileage, accessible OBD port, household with vehicles newer than 1996). In addition, the surveys allowed us to capture information about the households such as commute location, charger access, sensitivity to price, demographics, etc. We invited participants to take the internet-based survey in three different methods. First, CARB sent email invitations to ZEV owners who had applied for the California Vehicle Rebate Project (CVRP); second, CARB sent postcards to a random selection of persons who had a ZEV registered based on the DMV records but did not apply for CVRP; and third, CARB sent postcards to a random selection of owners of used PEVs based on DMV records. The result of the surveys and the total response rate were estimated, based on the DMV records, for the total number of light duty vehicles and plug-in vehicles by region and year, based on model year for vehicles model 2010-2017. Updated VMT records allow for re-evaluation of the survey data and logger data representation of the state light duty fleet, comprised of light duty vehicles, plug in vehicles, and new and used vehicles. The DMV data allow us to estimate the total number of ZEV on the road each year, in addition to the information about new vehicles sold based on the CVRP application.

21,000 new PEV owners and lessees started our survey between May 2015 and August 2018 in addition to 680 used PEV owners. Of those surveyed, 12,396 PEV households and 470 FCV households had enough information, answered all parts of the survey, and indicated that we could contact them for the logging phase, but this number included surveys with missing information for some survey part based on our skip logic or households that owned a vehicle that was incompatible with the loggers. The overall response rate to the surveys was 18%, and 82% of these respondents completed the survey. However, this 82% included persons who were not eligible for the logging study because they utilized their PEV for business purposes, no longer owned a PEV, and similar cases.

2.1 Logger Installation Process

The combined project design called for a straightforward process. After identifying potential households for the logging part of the study, we emailed those households to reaffirm their interest, that they still had the PEV, and that they planned to have it for the next 12 months. Of the households we invited, 15–25% agreed to participate and moved to the next phase. The overall rate of recruitment was 1 logger installation for every 300 households that received the initial survey.

The project was budgeted to allow two visits to each household, one to install loggers on all household vehicles and another to remove them. The initial plan also called for the project team to make one trip per region to do all installations in that region and a second trip to do all the removals. The regions included areas from San Diego in the south to Crescent City in the north, and the project team was based in Davis. The installation-removal team included the project researchers, a full-time project manager, part time staff member, and 16 undergraduate students.

The loggers for this project were obtained from FleetCarma, a vendor selected by a bid conducted by UC Davis. FleetCarma's OBD loggers (C2 and C5) are configured to collect real-time data with automatic data upload via the cellular network and contain internal GPS, making them the ideal data loggers for capturing vehicle data. Each logger had to be programed to a specific ZEV model, a process that was done manually at the beginning of the project and through the logger's internet connection later. The data collected by the loggers was analyzed and then sent by cellular connection to the vendor servers and from there to UC Davis servers.

By the end of the project we had to make many more trips to each region than what was originally planned for and budgeted. The main reason for this difference between the planned and actual execution was the difficulty of scheduling installations during weekdays, when people had their vehicle or vehicles away from home (e.g., at work). As a result, evenings and weekends were often the only times when we could install, and later remove, loggers in all the household vehicles at once. Other than these limitations on workable time windows, we underestimated the number of additional visits that would be necessary beyond the initial installation and final removal of the loggers. Over the project period we had to replace more than 30 faulty loggers or data cables, we had to remove loggers from vehicles owned by households who chose to leave the study, sold the vehicle, had an accident, moved out of the state, etc. In many cases, we recruited an additional household to maintain the total sample size. We had to make approximately 25 trips to Los Angeles, 20 to the San Diego area, 200 to the Bay Area, 50 to the Sacramento area, and 25 to the regions north and east of Davis.

The participation incentive was $350 split between the installation ($150) and completion of the data collection and return of the data logger ($200). Overall, we had to pay incentives to about 80% more households than the number used in this final report and visit each household 4–6 times instead of the 2 times planned. We recruited 424 Households and installed loggers at 402 vehicles, including 14 FCVs, 388 PEVs, and about 300 ICEVs. We dropped vehicles with data collected for less than 90 days, all with a sample of less than 4 vehicles of the same model.

Figure 4 presents the number of installations along the study timeline, including information on the model of ZEVs that had loggers installed. To reduce the project cost, we reinstalled the loggers from phase 1.0 in phase 2.0 vehicles, those from phase 1.5 in phase 2.5 vehicles, and those from phase 3 in phase 4 vehicles. Therefore, this final project report includes data collected between June 2015 and May 2020 for some part of the analysis. As Of July 2020, we continue to collect data from about 30 households as we are unable to uninstall the loggers due to the stay at home order resulting from the COVID-19 global pandemic. We hope that this data will be used in a future project to study travel behavior of electric vehicle owners in the time of Coronavirus.

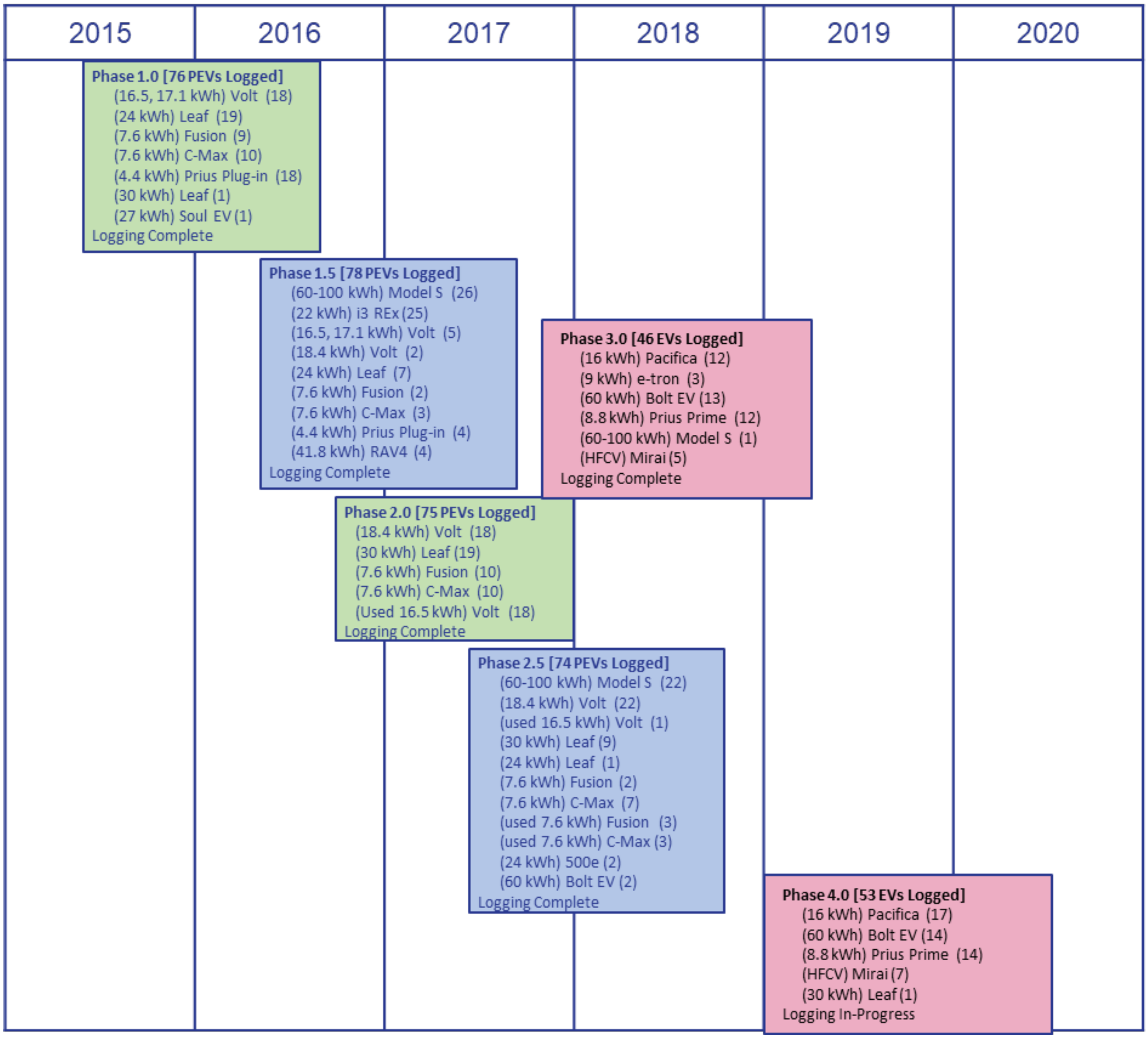


Figure 4. Overview of Number of Logger Installations During Each Phase of the Project, Classified by Number and Type (New or Used) of Vehicles per Household. MUD= multi-unit dwelling

We planned the recruitment to cover the main vehicle models at the time of each phase and to cover the shift from buyers of new PEVs to buyers of used PEVs and households with two PEVs. We also covered all main electric utilities in California. However, due to the extended period of data collection 2015–2020, the relatively small sample, and logger problems that forced us to drop some of the samples, we experienced a limitation in having statistically significant results in every category needed to fully represent the changing ZEV owner population.

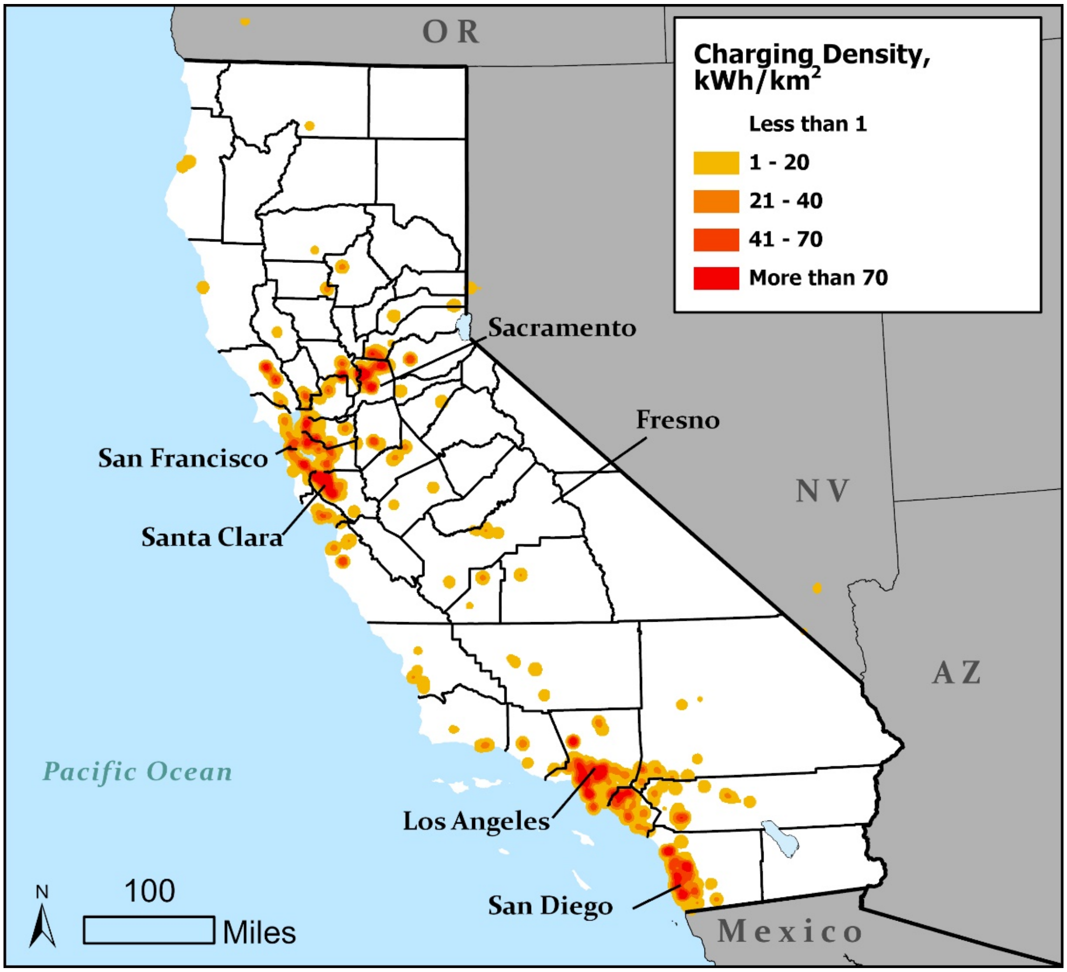


Figure 5. Home and Daytime Charging Locations 2015-2020

2.2 Data Collection and Limitations

As for all social science studies, this work suffers from self-selection bias resulting from the recruitment being based on survey takers who volunteered for the logging phase. We controlled for basic social demographic characteristics, but we could not control for any correlation between the probability to take a survey and volunteer for the study and specific driving and charging behavior. Another important bias in the household selection and the results presented is the fact that no participants were chosen who did not plug in their PEV on a regular basis. On the other hand, the self-selection of vehicle model by the households, for example users with lower daily miles select short range vehicles, is not a bias but a representation of the vehicle owners' population. To explore the potential bias of our selection please refer to a paper we published based on the servey response (Chakraborty, et. al 2020). For both the PEVs and the ICEs in the study, not all logger parameters were available on all vehicle models and the parameters collected changed over time with changes made by the logger vendor to the dataset design, the logger hardware, and the vehicle software. In general, the relevant set of parameters collected varied between the ICEs, the BEVs and the PHEVs due to differences in fuel sources. Other than speed and GPS metrics which were collected for all vehicles, the ICE data includes vehicle parameters such as fuel rate, mass air flow, etc. to calculate fuel consumption, the BEV data includes attributes such as battery voltage and power to estimate electrical enery consumption and the PHEV data contains both fuel and electrical energy determining metrics.

The data transferred from the logger includes raw data from the vehicles and calculated data based on algorithms programmed in the loggers. Some parameters, such as miles per gallon (MPG), are derived from multiple parameters such as revolutions per minute (RPM), engine load, mass air flow, and intake air temperature. Other parameters, such as distance, were derived from speed and time. Most parameters were collected every second but others, such as GPS and State of Charge (SOC), were collected every 10 seconds. Battery capacity was derived for each vehicle individually based on the average value, over the data collection period of SOC change and energy used. We did not use the manufacturer stated capacity or EPA range in our analysis.

One of the most important limitations of the data is that if one of the parameters being recorded changed, a new row would be generated in the dataset/spreadsheet and values for all the parameters would be populated in that row. However, because different parameters were recorded at different rates, a parameter that had the same value between adjacent rows may have been updated and had truly stayed the same over two collection times, or it may not yet have been updated and the program had populated the cell with the last recorded value from the previous row. In summary, although we attempted to resolve limitations within our study, due to the unreliability of certain data, it was not possible to distinguish whether an unchanged parameter was copied from the last collection time or recollected but had the same value.

Another limitation in the data collection was that data from ICEVs. First, our ICEVs sample includes only vehicles in households with one PEV or FCV that are, in most cases, newer than the ICEV and therefore are not a representative sample for ICEVs in California. Second, ICEVs within a given household that were estimated to be driven less than 1000 miles per year did not have loggers installed. Thus, logger data was not collected from these vehicles. However, the VMT on these ICEVs was recorded manually from odometer readings with only one vehicle exceeding 1000 miles.

We developed four different methods to estimate energy consumption from PHEVs (and ICEVs) based on the data reported for each vehicle. Overall, we identified a wide variation of results based on trip distance, speed, etc.

2.3 Data Annualization

While collecting vehicle data, the vehicle loggers sometimes malfunctioned due to internal software issues or external mishandling, leading to gaps in the time series data we received. If we analyzed the data without accounting for these gaps, we would be underestimating the annualized values of key vehicle metrics. Therefore, we developed a process to annualize vehicle metrics, while minimizing the miscalculation associated with this incomplete data issue to the best of our ability. For annualizing vehicle-level metrics for a given car, we first condensed the vehicle's events into days – this includes all days between the vehicle's first logging event to its last logging event. Next, we identified major gaps (more than 7 days) within the data collected by locating the dates and times when the vehicle logger didn't record any data. We then contacted the driver(s) of the car to gauge If the car was indeed not used during those identified gap days or if the logger simply malfunctioned. We marked the vehicle's days for which we knew the logger malfunctioned as invalid, given those days do not represent real travel behavior. Finally, we scaled the vehicle's totalized metrics to 365 days based on the number of valid logged days to attain annualized estimates of those metrics.

Similarly, for annualizing the metrics of a given household, we first condensed the events from each vehicle within that household into days (separately). Next, we located gaps within the data collected for each vehicle in the household. We then contacted the driver(s) of the vehicles to gauge If the vehicles were not being used during their identified gap days or if their loggers were simply malfunctioning. We marked all the vehicles' days for which we knew at least one vehicle's logger malfunctioned as invalid, since those days do not accurately capture real household travel behavior. Lastly, we merged the days data of all the vehicles and scaled the household's totalized metrics to 365 days based on the number of valid households logged days to attain annualized estimates of those metrics. In many cases, not all the vehicles within a household began or ended logging data at the same time; to handle data gaps introduced by mismatched start/end logging dates, we decided that the start date for the household days data is the start date of the vehicle in the household that started logging the latest, while the end date for the days data is the end date of the vehicle in the household that ended logging first. We did not directly account for weekday/weekend differences or seasonal variation while annualizing both vehicle and household metrics as we log data from all four seasons, for around 365 days for most of the household vehicles in our sample.

2.4 Sampling of the Logged Participant Households

The distribution of households was selected by electric utility and generally follows the market for electric vehicles with most participants being in one of the four largest metropolitan regions in California: San Francisco, Sacramento, Los Angeles, and San Diego. Some participants were in exceptional locations, such as in the mountains or along the coast, where isolation or temperature may have had an impact on how they used their vehicles compared to those in major metropolitan regions. Although the sample size is small in those cases, interacting with them and observing their behavior presents the possibility for additional learning from the project. All the results presented in the report are based on the relevant sample and are not weighted, as we focused on the impact of different technology types and did not estimate total impact.

This survey's participants—PEV households who purchased or leased their vehicle in the last 4 years—differ from average Californian households. For the general population, less than one-third of households buy a new car every 3-5 years, according to the 2012 California Household Travel Survey (CHTS) (CalTrans 2013). To compare PEV buyers to the general population (based on the CHTS 2012), we combined the income distribution by vehicle type and purchase year.

Considering the market penetration of alternative fuel vehicles, many of the current ZEV owners are early adopters of the technology. As observed in cases of other technologies, early adopters may have unique characteristics compared to other new car buyers—age group, education level, and technology awareness, among others.

Table 1 presents the statistics on sociodemographics and vehicle models among the survey participants. The sample was stratified by income to represent the income of the larger survey sample. More than 80% of households had an income higher than the median income in California ($67,739 according to the Census American Community Survey 1-year survey) and the percentage of people with graduate or professional degrees was 48.7% (California statewide 12.3%). In our dataset, males tended to drive the PEV more than females in a household, and slightly more BEVs were driven than PHEVs. More than 80% of respondents owned their houses, and more than 80% lived in detached units. About 50% of respondents had the Chevrolet Volt, Tesla (Model S-60_80 or Model S-80_100), or the Nissan Leaf, and a considerable number of the rest used the Prius Plug-in-4.4 or the Bolt-60.

Table 1. Sociodemographics and Vehicle Types Among the Usable Surveyed Participants

Income		Age		Education	
<50K	217	10-19 years old	11	High school	995
50-99K	1,064	20-29 years old	326	College	3,247
100-149K	1,686	30-39 years old	1,767	Post-graduate	4,059
150-199K	1,529	40-49 years old	2,166	**Gender**	
200-249K	1013	50-59 years old	1,932	Male	6,201
250-299K	667	60-69 years old	1,428	Female	2,052
300-350K	368	70-79 years old	554	Decline to state	77
350-399K	206	> 80 years old	74	**Household size**	
400-449K	154	Missing	79	1 person	868
450-499K	105			2 persons	3,236
> 500K	363			3 persons	1,523
				4 persons	2,021
				5+	706

Number of Vehicles		Types of ZEV		Model	
1	1000	Battery	4,230	500e	160
2	4,303	Plug-in Hybrid	3,749	Bolt-60	748
3	2,049	Fuel cell vehicle	375	C-Max Energi	480
4	694	**Purchase or Lease**		e-Golf	472
5+	290	Purchased	3,812	Fusion Energi	377
Number of drivers		Leased	4,202	i3	590
1	1,101	**Housing types**		Leaf	1,175
2	2,692	Own houses	6,998	Prius Plug-in	792
3	971	Rent or others	1,337	Tesla	1,384
4	486	**Detached housing**		Volt	1,442
5+	86	Detached	6,751	Others	391
		Others	1,585	Mirai	334

Table 1 presents the distributions of income, household size, and number of vehicles per household among the survey population. We tried to select households for logging that would reflect the geographic distribution and sociodemographic distribution of ZEV households as reflected in the initial survey.

Figure 6. Distribution of Household Income Among Survey Respondents and Logged Households

Overall, the logged households are similar to the surveyed households, other than having a minor oversampling of households with incomes of $50k-$100k and households with two vehicles.

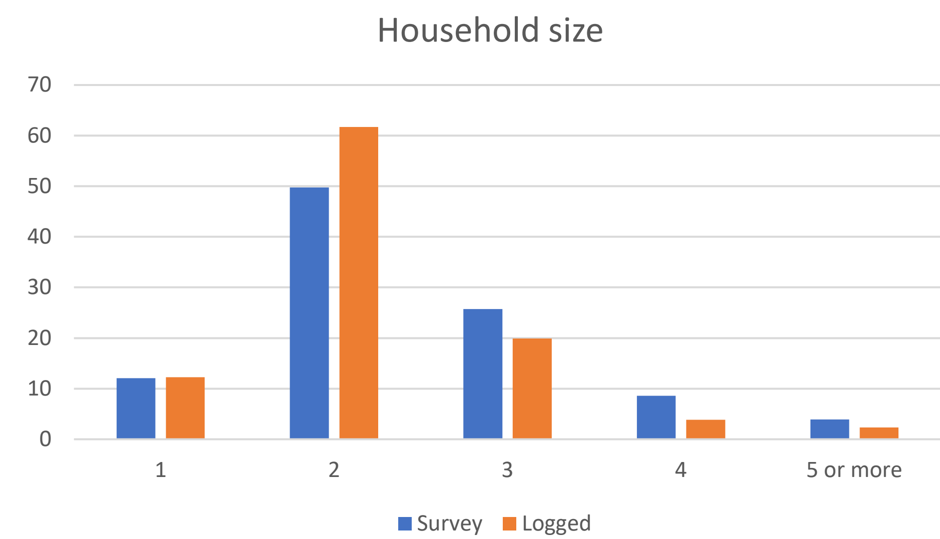


Figure 7. Distrubution of Household Size Among Survey Respondents and Logged Households

The main difference between the logged households and the survey and general populations that is not reflected in the sampling methods is the exclusion of PHEV users who are not plugging in their vehicles. Our 2014 research article suggests that short-range PHEVs are more likely to be used as conventional hybrids (Tal et al. 2014). A more recent study suggests that about a third of the short-range secondary PHEV owners who finished the survey are using the vehicle as a hybrid only without pluging in. (Turrentine, Tal, and Rapson 2018)

For the Toyota Mirai we had to recruit three households for every working loggers becouse of loggers rialbility problems and becouse of the small sample we did not aim for a reprasentative sample.

Table 2. Battery Capacity and Vehicle Types Among the Logged Participants

Make Model and Battery Capacity	Vehicle Type	Number of Vehicles	Major data collection period
Nissan Leaf-24 kwh	BEV	29	2015-2017
Nissan Leaf-30 kwh	BEV	28	2016-2018
Toyota RAV4 EV-42 kwh	BEV	5	2016-2017
Chevrolet Bolt-60 kwh	BEV	27	2017-2020
Tesla Model S-60_80 kwh	BEV	23	2016-2019
Tesla Model S-80_100 kwh	BEV	25	2016-2019

Make Model and Battery Capacity	Vehicle Type	Number of Vehicles	Major data collection period
Toyota Prius Plug-in-4.4 kwh	PHEV	22	2015-2016
Ford C-Max/Fusion-7.6 kwh	PHEV	60	2015-2018
Toyota Prius Prime-8.8 kwh	PHEV	27	2017-2020
Chrysler Pacifica-16 kwh	PHEV	28	2019-2020
Chevrolet Volt-16 kwh	PHEV	44	2015-2017
Chevrolet Volt-18 kwh	PHEV	40	2017-2019
Toyota Mirai	FCV	11	2018-2020
Total	-	369	-

Throughout this report, letters are used in figures to identify significant differences between the average usage characteristics of different vehicle models among logged vehicles. These significance tests are performed using the Tukey-Kramer range test for groups of unequal sizes (Tukey, 1977); this method is commonly used to identify pairwise differences between groups when a one-way ANOVA test confirms that a significant difference exists in the data. In charts where these letters are used to indicate significance, each vehicle model will have one or more letters. If two models share any of the same letters, the test does not identify a significant difference between them for the variable in question; if not, the test does find a significant difference. For example, consider a chart showing the mean efficiency for three vehicle models: if model 1 has the lowest mean and is marked with the letter *a*, model 2 has the middle mean and is marked with the letters *ab*, and model 3 has the highest mean and is market with the letter *b*, then the pairwise mean comparison finds a significant difference between models 1 and 3 but not between model 2 and either of the other models.

2.5 PHEV eVMT Calculation

Attributing vehicle miles travelled (VMT) to either electricity (eVMT) or gasoline (gVMT) in an ICEV or BEV or FCV is trivial, all the VMT fall into either one or the other category; however, PHEVs have two energy sources and correctly tracking the energy can be challenging when both sources are used during a trip. The following sections describe the methodology used to calculate eVMT for PHEVs.

2.5.1 Need for Energy Efficiency Ratio

One obvious way of calculating the portion of VMT that should be attributed to eVMT would be to calculate the ratio of total electrical energy consumed to the total energy consumed for both gasoline and electric, and multiply this ratio by the total VMT. The problem with this approach is that energy consumption for the two sources does not yield the same number of miles. For example, the 2011 Chevy Volt has an EPA rated 37 MPG on gasoline and a 93 MPGe when running purely electric. That means that for every kWh of electricity the Volt can travel over 2.5 times as far as with the equivalent energy in gasoline.

To correct for this, an Energy Efficiency Ratio (EER) needed to be calculated for comparing the electrical and gasoline usage of energy. Ideally the EER would be calculated for every operating condition of the vehicle (i.e., every combination of vehicle speed, engine speed, engine torque, motor speed, motor torque, battery SOC, etc.). However, since this approach is not practical, a single EER was calculated based upon the vehicle type. The combined fuel economy numbers from fueleconomy.gov was used for calculating the EER. The EER was calculated by dividing the all-electric fuel economy in MPGe by the gasoline-only fuel economy in MPG. For example, the 2011 Chevy Volt described previously would have an EER of 2.5 (93 MPGe / 37MPG). The calculated EER was used to adjust the electrical energy consumed by the vehicle before calculating the ratio of electrical energy consumed to total (gas and electric).

Equation 1 shows the calculation of the EER; Equation 2, the calculation of the gasoline equivalent electrical energy consumption; and Equation 3, the calculation of eVMT.

Equation 1. EER Equation

$$EER = \frac{MPGe_{EPA}}{MPG_{EPA}},$$

where $MPGe_{EPA}$ is the EPA electric only fuel economy and MPG_{EPA} is the EPA combined highway and city fuel economy for the vehicle using gasoline only.

Equation 2. Electrical Energy Consumption to Gasoline Equivalent

$$E_{ElecGE} = EER \cdot E_{Elec},$$

where E_{Elec} is the measured electric energy consumption and E_{ElecGE} is the gasoline equivalent electrical energy consumption.

Equation 3. eVMT Calculation

$$eVMT = VMT\frac{E_{ElecGE}}{E_{ElecGE} + E_{Gas}},$$

where E_{ElecGE} is the value calculated from Equation 2 and E_{Gas} is the measured gasoline energy consumption.

2.5.2 Adjusting for Battery Efficiency

The eVMT calculated using Equation 3 is dependent upon the calculation of E_{ElecGE}, which in turn is dependent upon the measurement (or calculation) of E_{Elec}. One may intuitively think that the E_{Elec} value should not be calculated, but directly measured by integrating the power in and out of the battery. However, this approach would not be correct because batteries are not 100% efficient. Energy is lost when it is either put into or taken out of the battery. To correct for this, the energy consumed (energy taken from the battery) and energy produced (energy put into the battery) are maintained separately and an efficiency factor is applied to the energy produced.

Equation 4 is the equation for calculating the electrical energy consumed. Ideally the battery efficiency should be determined by testing each individual vehicle, and will vary with temperature, rate of power draw, age of the battery, etc. Since this approach would not be practical, a 90% battery efficiency was used for all vehicles. The 90% efficiency was based on a linear fit of data analyzed for energy consumed, energy produced, and delta SOC.

Equation 4. Electrical energy consumption calculation

$$E_{Elec} = E_{BattCon} - Eff_{Batt} \cdot E_{BattProd} \ ,$$

where $E_{BattCon}$ and $E_{BattProd}$ are the energy consumed and produced measured at the battery, and Eff_{Batt} is the battery efficiency.

2.5.3 eVMT Before Engine On

The eVMT calculation for the equations provided thus far apply a fraction of the VMT to eVMT on a trip basis. While this approach is valid, further improvements can be made to increase the accuracy of the calculations by addressing other variables that could influence eVMT. For example, one such variable is that during a single trip the driving conditions (as well as vehicle efficiency) may vary dramatically and therefore the use of energy consumption alone may not accurately attribute VMT to gasoline or electric. It was observed that all the miles traveled prior to the first engine-on event were eVMT, where the miles travelled after the first engine-on were a blend of gVMT and eVMT. It was this observation that prompted the change to Equation 3. Equation 5 is the updated eVMT equation (Equation 3) that attributes 100% of miles traveled to eVMT prior to the first engine-on event, and the fraction of the miles after to eVMT based upon the fraction of energy.

Equation 5. Updated eVMT calculation

$$eVMT = VMT_{EngOn} + \left(VMT - VMT_{EngOn}\right)\frac{E_{ElecGEAEO}}{E_{ElecGEAEO} + E_{Gas}} \ ,$$

where VMT_{EngOn} is the VMT at the first engine-on, and $E_{ElecGEAEO}$ is the gasoline equivalent electrical energy consumption after the engine is first turned on.

2.5.4 Adjusting for Kinetic Energy

The initial eVMT equation provided assumed that it was on a trip basis, so the vehicle both starts and ends at rest. However, the starting point of the hybrid mode may not be at rest, therefore, in the updated eVMT equation (Equation 5), the $E_{ElecGEAEO}$ accounts for the kinetic energy of the vehicle. The kinetic energy of the vehicle, when it is moving and the engine is on, will carry the vehicle some further distance. One may wonder if this energy is significant or not. Consider a 2011 Chevy Volt with a curb weight of 3,781 lbs carrying 200 lbs (passenger and cargo) at 80 mph, the kinetic energy in the vehicle would be 1.15MJ or 0.32kWh which is equivalent to approximately 3% of the 10.9kWh of usable battery capacity. This amount of energy would propel the vehicle 0.89 mi according to the EPA all-electric fuel economy for the Volt (before any adjustments for battery and motor efficiencies). Considering that the measured median trip distance for Volts was 5.35 mi the 0.89 mi represents approximately 16.6% of the median trip length. PHEVs with smaller battery packs will potentially have a higher percentage of the usable battery capacity converted into kinetic energy. This is because the kinetic energy of a vehicle is related to the mass of the vehicle, and there is not a 1:1 scaling of vehicle mass to battery capacity. A doubling in battery capacity will roughly double the mass of the battery pack, but this will not double the mass of the vehicle.

Equation 6 is the equation for kinetic energy.

Equation 7 is the calculation for the gasoline equivalent electric energy at engine-on. The kinetic energy is divided by Eff_{Motor} which is the assumed motor efficiency of 90%. The 90% motor effieciency was chosen as it provided a simple round number that was in line with published motor efficiencies and fit the data that had been collected. The energy consumed at the battery would be higher than the output of the electric motor and must be accounted for.

Equation 6. Kinetic Energy Calculation

$$E_{Kin} = \frac{1}{2} m v_{AEO}^2 \ ,$$

where *m* is the mass of the vehicle (assumed to be curb weight plus 200lbs), and v_{AEO} is the velocity of the vehicle at engine-on.

Equation 7. Electric Energy Gasoline Equivalent at Engine-On

$$E_{ElecG\,EAEO} = EER \cdot \left(E_{Elec} + \frac{E_{Kin}}{Eff_{Motor}} \right),$$

where Eff_{Motor} is the motor efficiency, which was assumed to be 90%.

3 Logger Data: Vehicle Level Analysis of PEVs

In this section, we present our results and observations on PEV usage at the vehicle level using data collected from the loggers. In total, **137 BEVs, 221 PHEVs, and 11 FCVs**. 23 BMW i3 REX had trouble acquiring data and were dropped from our analysis. There was one Kia Soul (111 mile range) and one Fiat 500e (84 mile range), which were also dropped for our analysis due to exceptionally low sample size. The other vehicles have reliable data for most parameters, have reliable data for longer than 120 days, and can be considered for the analysis. They are considered in the vehicle level analysis presented in this section. To take advantage of the wealth of vehicle-usage information, all the remaining PEVs were considered in the vehicle-level analysis. The sample size of vehicles and households used in the household level analysis is provided in the following section. All the descriptive analyses and related summary statistics summarized in **Table 3** to **Table 14** are from the loggers. Likewise, the descriptive analyses and related summary statistics depicted in **Figure 8** to **Figure 54** are from the loggers.

3.1 Data Description

Table 3-**Table 29** summarize, respectively, the data collected on BEV driving, BEV charging, PHEV driving, PHEV charging, FCV driving and FCV refueling from the loggers. The summaries include vehicle data, spanning approximately 1 year for each logged car, collected over the five year course of this study. More granular breakdowns of the PEV driving and charging summaries are provided in following chapters. From the raw data, which includes noticeably short trip events of zero to a few hundred yards, we used a filtering criteria of 1 km to denote a valid trip for PHEVs, BEVs and FCVs. The filtering criteria of 1 km is based on filtering out GPS noise and extemely short trips registered at the loggers with no energy use and the rule of thumb values for acceptable walking distances (Smith and Butcher 2008; Yang and Diez-Roux 2012). For the charging sessions, a cutoff of 1 kWh for the BEVs and 0.25 kWh for the PHEVs was used. In addition, we filtered out trips and charging sessions that did not report variables that are usually included for this type of vehicle such as: battery SOC, distance traveled, energy charged, and driving energy (electrical and gasoline) consumed. Overall, 99.8% of charging energy (PHEVs and BEVs), 99.7% of BEV VMT, 99.6% of PHEV VMT and 88% of FCV VMT were still retained after filtering. We further classified the BEVs into 6 types based on the battery capacity: Leaf-24, Leaf-30, RAV4 EV-42,

Bolt-60, Tesla Model S-60_80, and Tesla Model S-80_100. For the PHEVs, we adopted a similar approach and classified the PHEVs into 6 types: Prius Plug-in-4.4, C-Max/Fusion-7.6, Prius Prime-8.8, Pacifica-16, Volt-16, and Volt-18. Since both the Ford C-Max Energi and Fusion Energi 7.6 have the same battery capacity, we combined them together as C-Max/Fusion-7.6. Chevy Volts model year (MY) 2016 or later have bigger batteries than those of earlier model years and are classified as Volt-18. The rest of the Volts were classified as Volt-16.

Table 3. BEV Driving Data Overview

BEV Type	Number of Vehicles	Trips-Raw Data	Total VMT-Raw Data	Trips-Filtered Data	VMT-Filtered Data	Average Driving Days/Vehicle-Filtered Data
Leaf-24	29	40714	263645	34061	262210	264
Leaf-30	28	38488	268780	33435	267535	266
RAV4 EV-42	5	8775	60163	7716	60005	344
Bolt-60	27	47760	382603	39479	381032	295
Model S-60_80	23	24295	375573	21057	374908	279
Model S-80_100	25	22066	285046	20032	284682	241
All BEVs	137	182098	1635810	155780	1630372	272

Table 4. BEV Charging Data Overview

BEV Type	Number of Vehicles	Charging Sessions-Raw Data	Total kWh-Raw Data	Charging Sessions-Filtered Data	Total kWh-Filtered Data	Average Charging Days/Vehicle-Filtered Data
Leaf-24	29	9211	57739	8707	57638	219
Leaf-30	28	6880	62836	6744	62804	185
RAV4 EV-42	5	1527	20003	1482	19993	253
Bolt-60	27	9434	100612	8351	100535	176
Model S-60_80	23	6994	139844	6737	139777	217
Model S-80_100	25	5079	106753	4902	106710	152
All BEVs	137	39125	487787	36923	487456	192

Table 5. PHEV Driving Data Overview

PHEV Type	Number of Vehicles	Trips-Raw Data	Total VMT-Raw Data	Trips-Filtered Data	VMT-Filtered Data	Average Driving Days/Vehicle-Filtered Data
Prius Plug-in-4.4	22	36915	315465	31473	314231	312
C-Max/Fusion-7.6	60	88796	729091	74971	726389	273
Prius Prime-8.8	27	42548	337533	37205	336465	301
Pacifica-16	28	39602	273916	34661	272970	238
Volt-16	44	60830	568379	51419	566354	291
Volt-18	40	56957	460974	49946	459257	299
All PHEVs	221	325648	2685359	279675	2675665	284

Table 6. PHEV Charging Data Overview

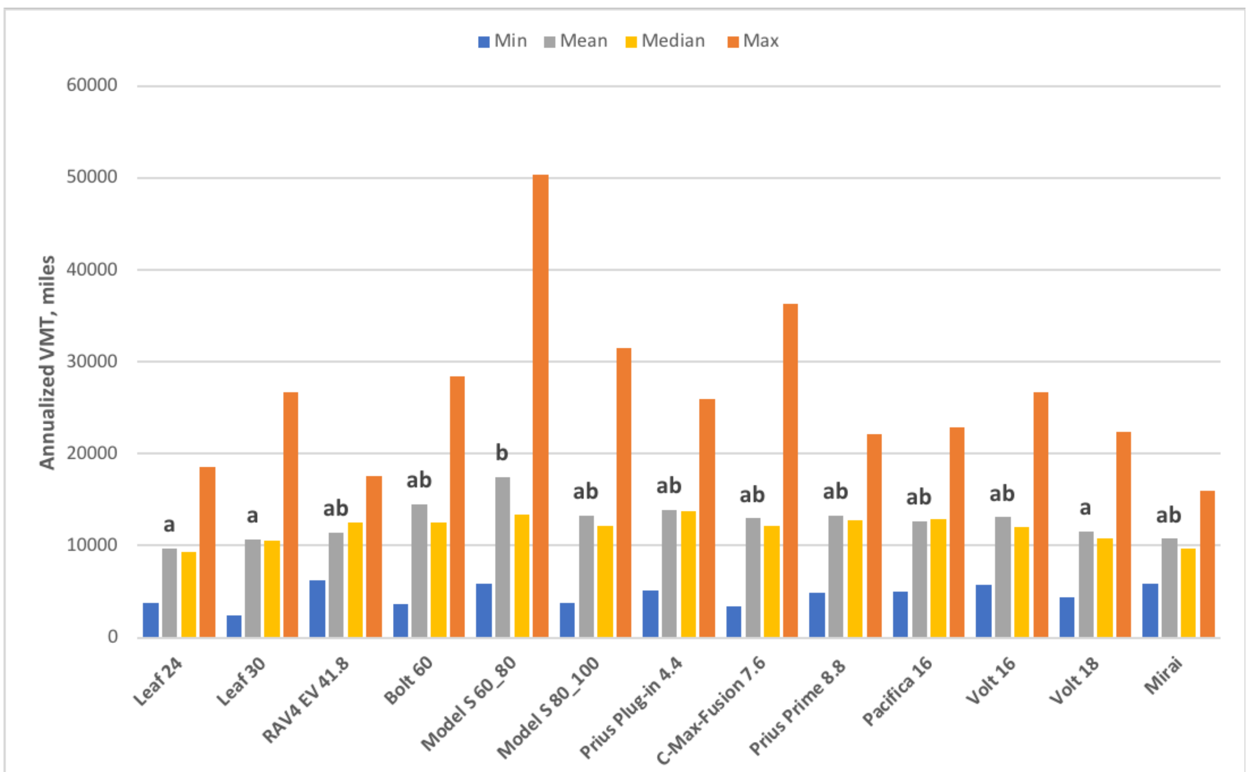
PHEV Type	Number of Vehicles	Charging Sessions-Raw Data	Total kWh-Raw Data	Charging Sessions-Filtered Data	Total kWh-Filtered Data	Average Charging Days/Vehicle-Filtered Data
Prius Plug-in-4.4	22	8101	17803	7700	17774	232
C-Max/Fusion-7.6	60	25267	76506	21727	76192	213
Prius Prime-8.8	27	9587	29975	8629	29948	226
Pacifica-16	28	10342	70338	9936	70301	199
Volt-16	44	26501	100008	15868	99949	251
Volt-18	40	14104	83679	11043	83621	213
All PHEVs	221	93902	378311	74903	377785	222

Table 7. FCV Driving Data Overview

FCV Type	Number of Vehicles	Trips- Raw Data	Total VMT- Raw Data	Trips- Filtered Data	Total VMT- Filtered Data	Average Driving Days/Vehicle- Filtered Data
Mirai	11	15301	104133	11327	91164	247

Table 8. FCV Refueling Data Overview

FCV Type	Number of Vehicles	Refueling Sessions	Total Hydrogen (kg)	Average Refueling Days/Vehicle
Mirai	11	408	823.40	20.67



*If two vehicle models' annualized VMT means do not share a letter, they are significantly different.

Figure 8. Average Annualized VMT by PEV Model

Table 9. Annualized VMT by Vehicle Types

Vehicle Type	Average	Standard Error	Median	Standard Deviation	Max
ICE	9009.7	308.5	8106.3	5560.8	37786.1
PHEV	12808.0	363.3	12080.6	5400.2	36273.1
BEV	12876.3	600.0	11722.6	7022.7	50326.6
SRBEV	10311.8	594.0	10017.3	4677.2	26642.5
LRBEV	14996.2	913.2	12502.4	7908.3	50326.6
FCV	10737.8	879.9	10148.4	3048.3	16009.5

Figure 8 and **Table 9** summarize descriptive statistics of annual VMT for all types of logged vehicles. On average, the BEVs had a slightly higher annualized VMT than the PHEVs. LRBEVs (Long-range BEVs) had the highest average and median annual VMT out of all vehicle technologies logged, even compared to the ICE. SRBEVs refer to short-range BEVs.

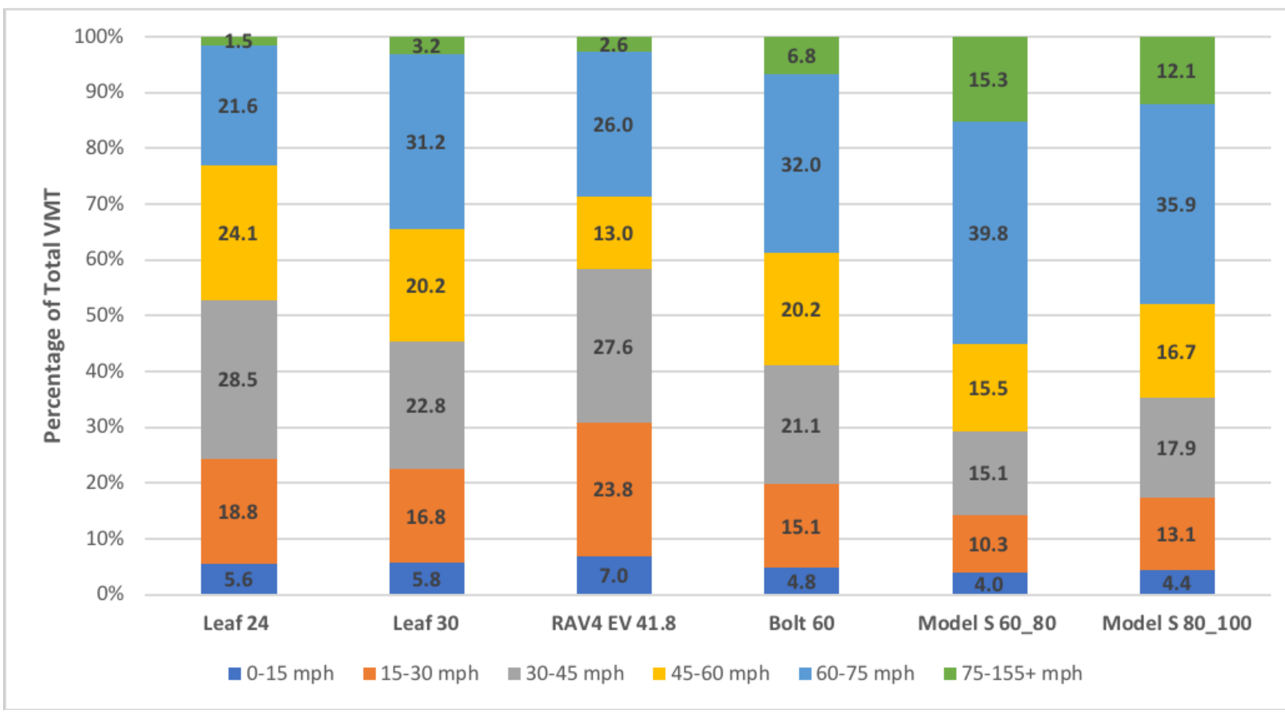


Figure 9. BEVs: Percentage Share of Total VMT by Trip Speed (in mph)

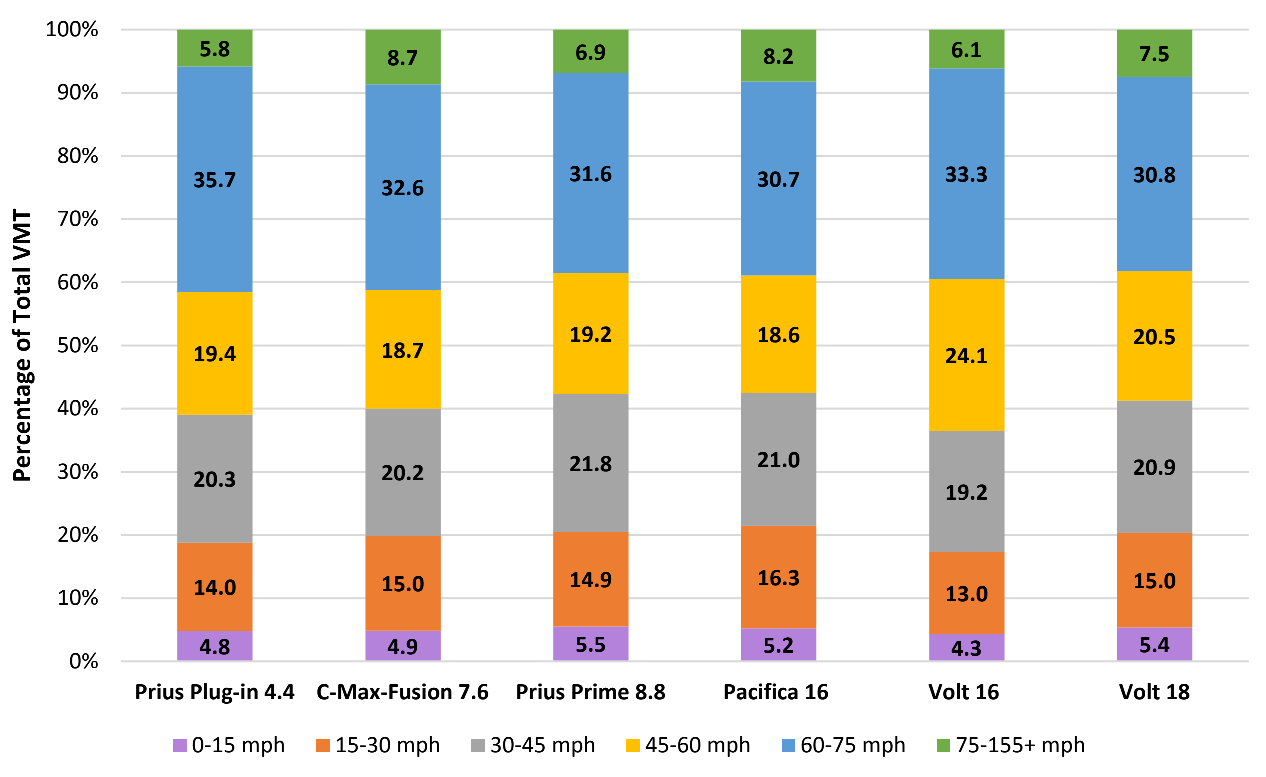


Figure 10. PHEVs: Percentage Share of Total VMT by Trip Speed (in mph)

Figure 9 and **Figure 10** show the share of total VMT by trip speed bin (the vehicle's driving speed) for BEVs and PHEVs, respectively. Compared to all other PEVs (Leaf, RAV4, Bolt, and all PHEV types), the Model S BEVs have a higher share of VMT at trip speeds 60 mph or faster. In fact, almost 50% of Model S total VMT was from trips at speeds of 60 mph or faster, whereas only around 15% of its VMT was from trips with speeds less than 30 mph. Furthermore, the high all-electric range (AER)/battery capacity could have contributed to the Model S having the highest share of VMT at very high speeds (75 mph or more) compared to all other PEVs. Among the PHEVs, there is a comparable share of VMT from trips driven at speeds of 60 mph or faster (about 40%) and from trips driven at speeds less than 45 mph (about 40%). At very high speeds (75 mph or more), Prius Plug-in-4.4 has the lowest share of total VMT, followed by Volt 16, Prius Prime-8.8, Volt 18, Pacifica 16, and C-Max/Fusion-7.6.

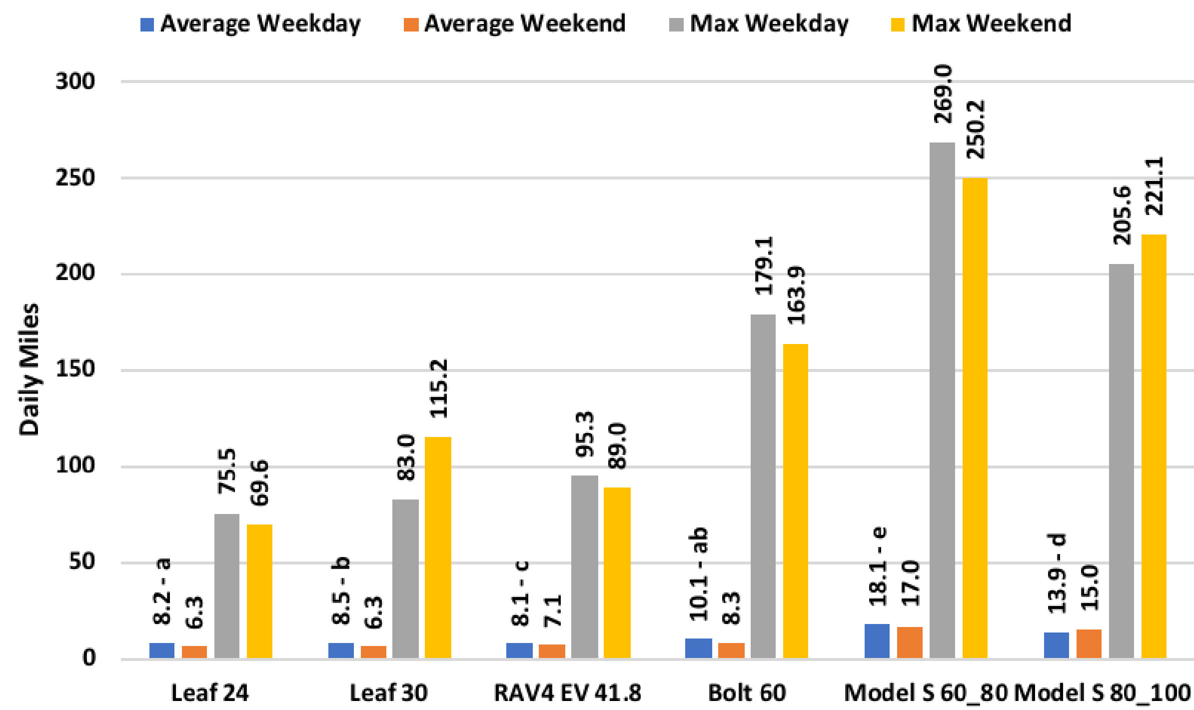
3.2 Battery Electric Vehicles Driving

As shown in **Table 10**, on average, the Leaf-24 and Leaf-30 drivers make more trips and drive shorter trip distances than do Tesla Model S-60_80 and Tesla Model S-80_100 BEV drivers. The average trip distance of the RAV4 EV-42 is comparable to that of the Leafs (Leaf-24 and Leaf-30). The average trip distance of the Model S BEVs (60_80 and 80_100) was almost twice that of the Leafs and RAV4 EV-42. The average trip distance of the Leafs did not vary much between weekdays and weekends. Except for the Leaf-30 and Tesla Model S-80_100 vehicles, the weekday maximum trip distance of Leaf-24, RAV4 EV-42, Bolt-60, and Tesla Model S-60_80 vehicles was higher than their respective weekend maximum trip distance (). More than half of the Leaf-24, Leaf-30, RAV4 EV-42 and Bolt-60 trips were less than 5 miles. About 15% of Tesla Model S-60_80 and Tesla Model S-80_100 trips were more than 30 miles, whereas around 95% of the Leaf-24, Leaf-30, RAV4 EV-42 and Bolt-60 trips were less than 30 miles (**Figure 12**). RAV4 EV-42 had the highest kWh/mile consumption for average trip speeds ranging from 15 mph to 75 mph.

Tesla Model S-60_80 and Tesla Model S-80_100 have significantly lower average kWh/mile consumption at higher trip speeds than their respective average kWH/mile consumption at lower trip speeds (**Figure 13**).

Table 10. BEV Driving Trip Level Summaries (on days when the BEV was driven)

BEV Type	Average Trips/Day	Average Trip Distance (miles)	Average kWh/Trip	Average kWh/Mile
Leaf-24	4.5	7.7	1.8	0.2
Leaf-30	4.5	8.0	2.1	0.3
RAV4 EV-42	4.5	7.8	2.9	0.4
Bolt-60	4.8	9.7	2.4	0.3
Model S-60_80	3.3	17.8	6.0	0.4
Model S-80_100	3.3	14.2	4.9	0.4
All BEVs	4.2	10.5	3.0	0.3



*If two vehicle models' weekday daily mile means do not share a letter, they are significantly different.

Figure 11. Average and Maximum Trip Distance on Weekdays and Weekends by BEV Type

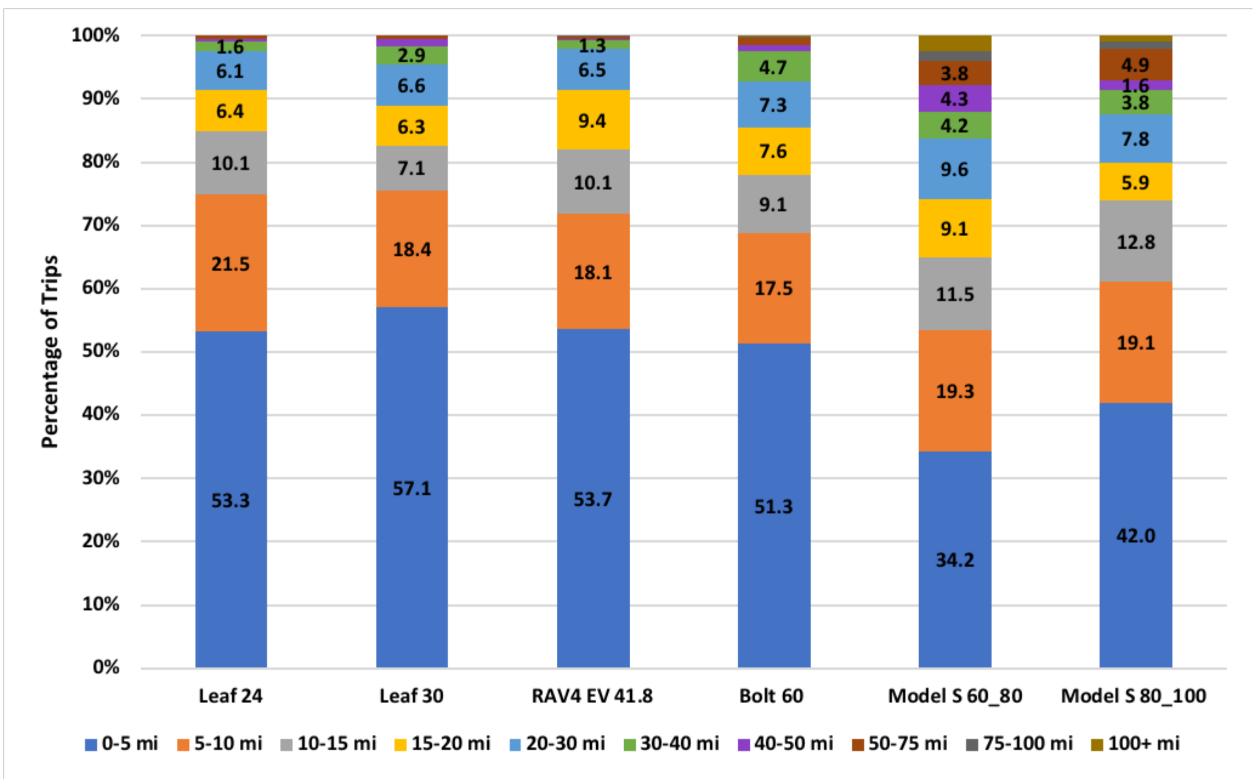


Figure 12. Percentage of Trips by Trip Distance Bins (miles) and by BEV Type

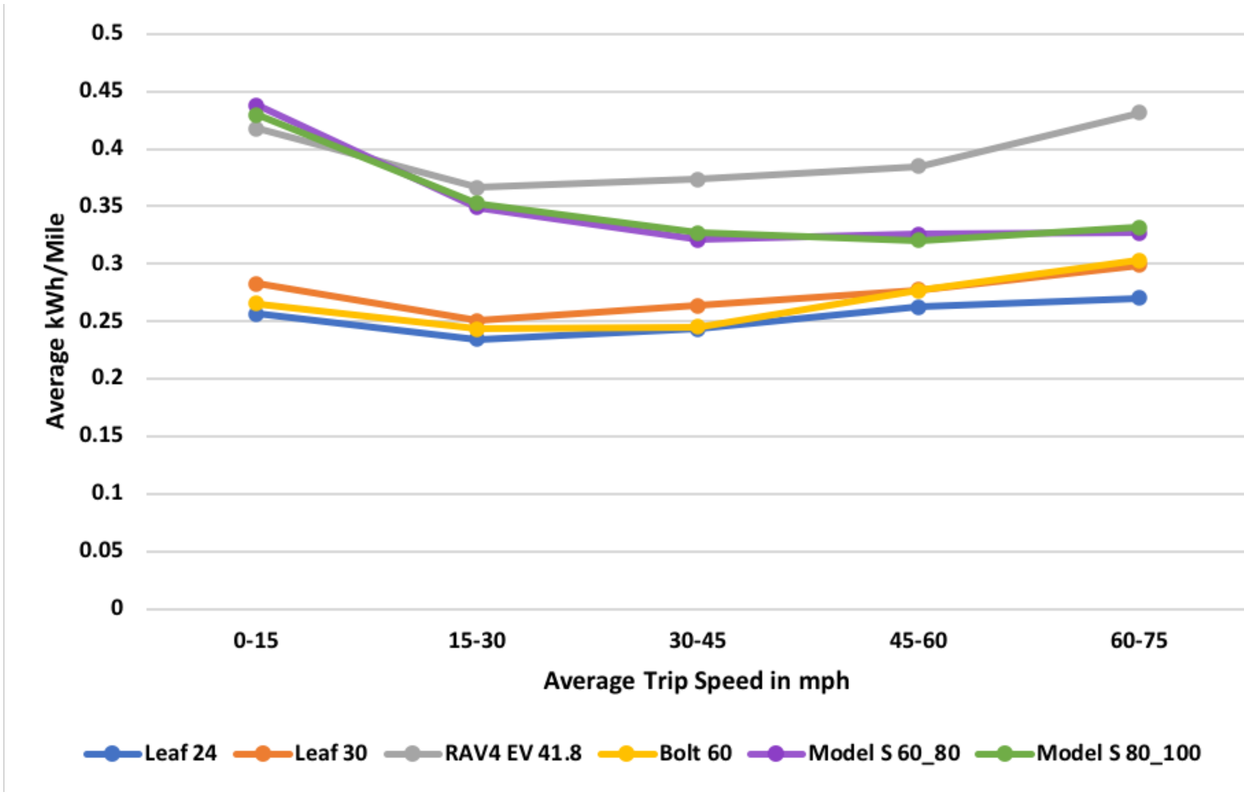
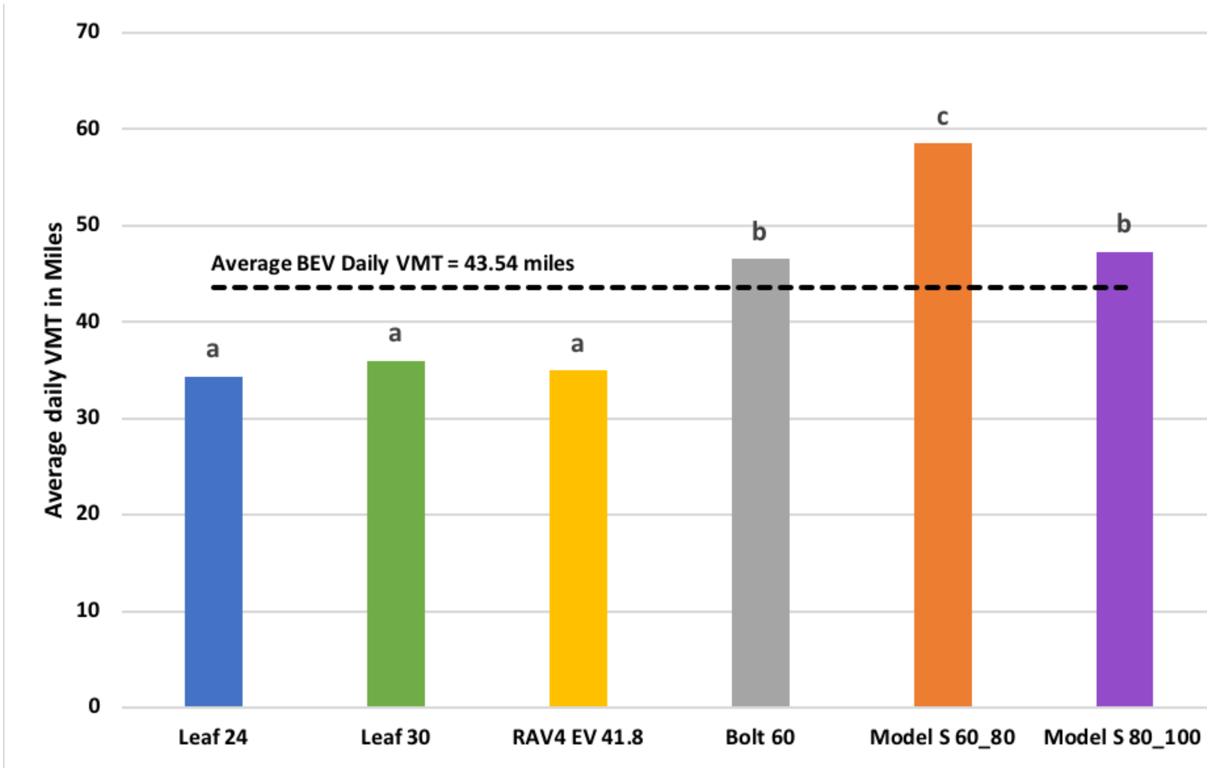


Figure 13. Effect of Speed on Energy Consumption per Mile



*If two vehicle models' VMT means do not share a letter, they are significantly different.

Figure 14. Average Daily VMT of the Individual BEVs by BEV Model

Figure 14 shows the average daily VMT of the individual BEVs. The average daily VMT of the Leaf-24, Leaf-30, and RAV4 EV-42 was less than the overall BEV fleet average daily VMT of 43.54 miles. The average daily VMT of the Bolt-60, Tesla Model S-60_80 and Tesla Model S-80_100 was greater than overall BEV fleet average daily VMT. Though the average daily VMT could be a useful and straightforward metric to compare how different BEVs utilize their All-Electric Range (AER), it could be quite misleading as we will illustrate in the following subsection.

3.2.1 Routine Destinations and Activity Spaces

In addition to their effect on daily and annual VMT and trip distance, battery capacity and AER have a strong impact on the number of different destinations BEVs are used to access and over how wide an area these destinations are spread. Short-range vehicles that are reliant on daily charging at one or more locations cannot be used as flexibly as longer-range vehicles that can go multiple days between charging events, and their owners are more likely to use an internal combustion engine vehicle as the household's primary means of transportation for long trips. Supplemental data to support this can be found in **Figure 76**. In this section, analysis of the importance of routine destinations on annual travel and of the total area covered by each vehicle's annual travel show that shorter-range BEVs are used largely for regular travel between home and a single other location whereas longer-range luxury BEVs are used to access a wider range of destinations spread over a much larger area.s The Bolt-60 in our sample, have usage patterns in between the shorter-range and longer-range BEVs, despite larger batteries and range similar to the shorter-range Tesla Model S.

An analysis of the common destinations visited by vehicles in this study that were supplied with GPS loggers indicated that shorter-range BEVs are mainly used for regular travel between home and a small number of routine destinations, whereas longer-range BEVs are used for less routine travel and are much more likely to be used for overnight travel away home. Routine locations were identified by clustering the spatial coordinates of the endpoints of all trips made by each vehicle using the Density-Based Spatial Clustering of Applications and Noise (DBSCAN) algorithm with a distance threshold of 250 meters and a cluster density threshold of 5 neighboring points. DBSCAN is commonly used to identify distinct locations from GPS points because this method clusters points based only on proximity rather than to populate a predetermined number of clusters and because it distinguishes between points that are part of a feature and "noise" points (Schubert et al., 2017). Across all vehicles in the study, 87.9% of destinations were classified as being in a cluster and 24.4% of destinations were classified as being in the most-visited cluster. Destinations within a single cluster were classified as being the same location, and points not within any cluster were classified as having been visited only once. For all vehicles, the most-visited location was also the last destination of almost every day, which indicates that it is a home location. Locations that were visited more than 12 times (approximately once per month) over the study period were classified as routine destinations for the purposes of this analysis. Monthly recurrence was chosen as the cutoff for routineness because it is near the maximum suggested duration for studies of routine activity space and routine travel behavior (Schönfelder & Axhausen, 2003; Zenk et al., 2018), but the results were similar when the threshold was set to visits every two weeks.

To analyze the relative significance of routine travel for vehicles of different ranges, each vehicle's annual VMT was partitioned based on whether any routine destinations were visited on the travel day. The four categories used for this analysis were *Primary nonhome destination*, which comprised days in which the vehicle started or ended the day at home and made at least one trip to the most common non-home destination; *Other routine nonhome destinations*, which comprised days in which the vehicle started or ended the day at home, did not visit the most common non-home destination, but visited another destination that was classified as routine; *No routine nonhome destinations*, which comprised days in which the vehicle started or ended the day at home but did not travel to any other routine destinations; and *Away from home area*, which included all travel on days in which the vehicle did not start or end at home.

The results of this partitioning are shown in **Figure 15**. In general, the most-visited destination is most important for short-range BEVs, and days with non-routine travel (both local and overnight) make up a much larger share of travel for longer-range BEVs. Interestingly, the Bolt-60 in the study showed a similar importance of routine travel as the Leafs, despite having as much range as some of the Teslas, which suggests that the size and comfort of the vehicles together with cast charging availability may influence the way these vehicles are used separate from the impact of battery capacity. For all vehicle types, the largest fraction of annual VMT occurred on days that included the most-common non-home destination (likely a commute location); this ranged from about 60% of annual VMT for the Leaf vehicles in the study to less than 40% of annual VMT for the Tesla Model S and RAV4 EV-42 vehicles. The smallest portion of travel for all vehicle types occurred on days in which none of the trips ended at home, but these days accounted for a much larger proportion of annual VMT for Tesla Model S vehicles (about 15%) than for Leaf and Bolt-60 vehicles (under 6%). Travel on non-commute days to locations visited at least once a month made up a similar share of VMT across all vehicle types, although it was slightly higher for the small number of RAV4 EV-42 in the study.

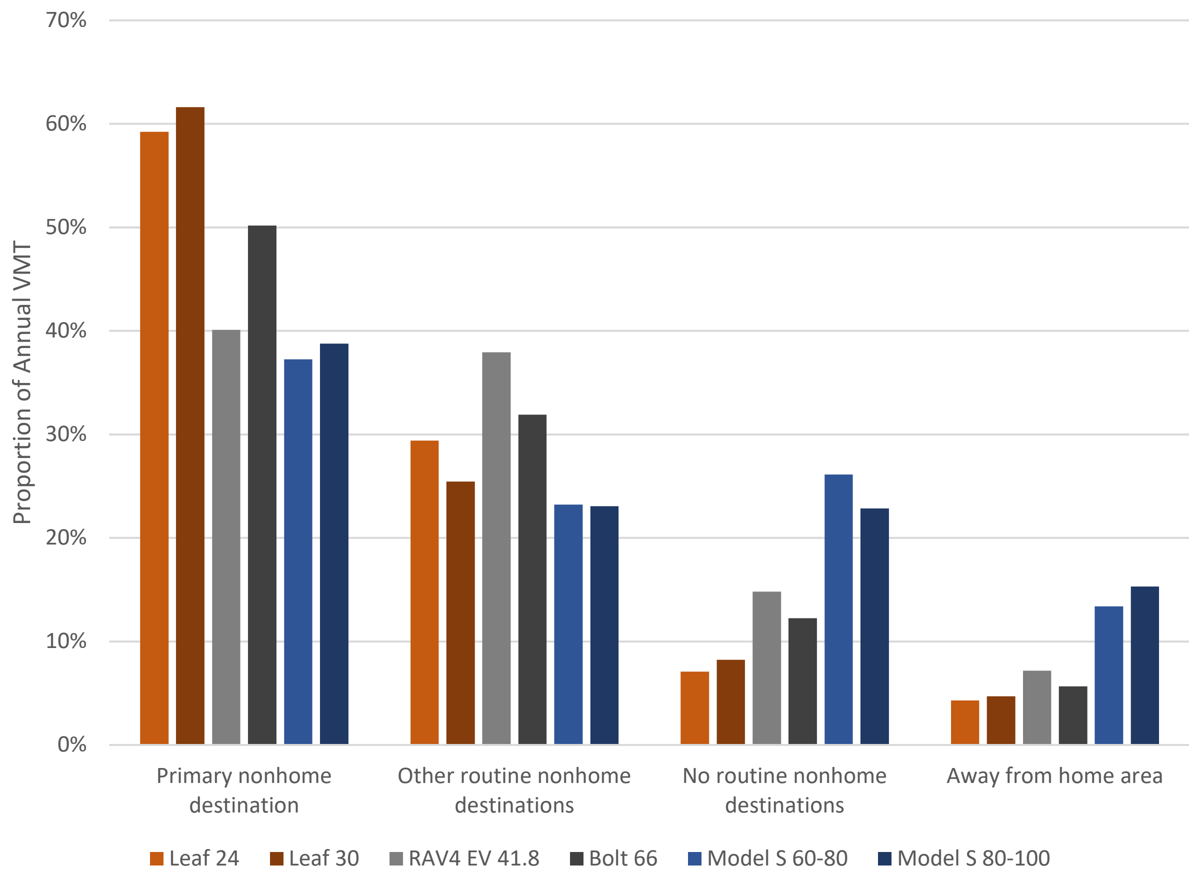


Figure 15. Proportion of annual VMT on days with and without routine destinations

Activity spaces are a geographic concept that are used to model the range of opportunities and interactions a person has access to during their habitual movements. Standard deviational ellipses (SDEs) are particularly useful for estimating activity spaces from GPS data both because they can be processed quickly without relying on secondary information about the road network and because they can be scaled to include an arbitrary proportion of destinations (Sherman et al., 2005). SDEs are constructed from a set of coordinates by identifying an axis on which the points vary most significantly and determining the standard deviation of the coordinates along that axis and a perpendicular axis. An ellipse is constructed with its center at the midpoint of the coordinates and its axes scaled to the standard deviations along the two rotated axes. For this analysis, we calculate SDEs with a radius of a single standard deviation to capture approximately 68% of each vehicle's destinations that are closest to the center and then compute the area of this ellipse in square miles. GPS coordinates with destinations spread over a larger geographic area will have larger SDEs, and those with fewer destinations will have smaller SDEs, even if those destinations are far apart. An example of an SDE computed from destinations visited by a Tesla driver is shown in **Figure 16**; note that the SDE covers their frequently visited destinations, but not their less-frequently visited ones.

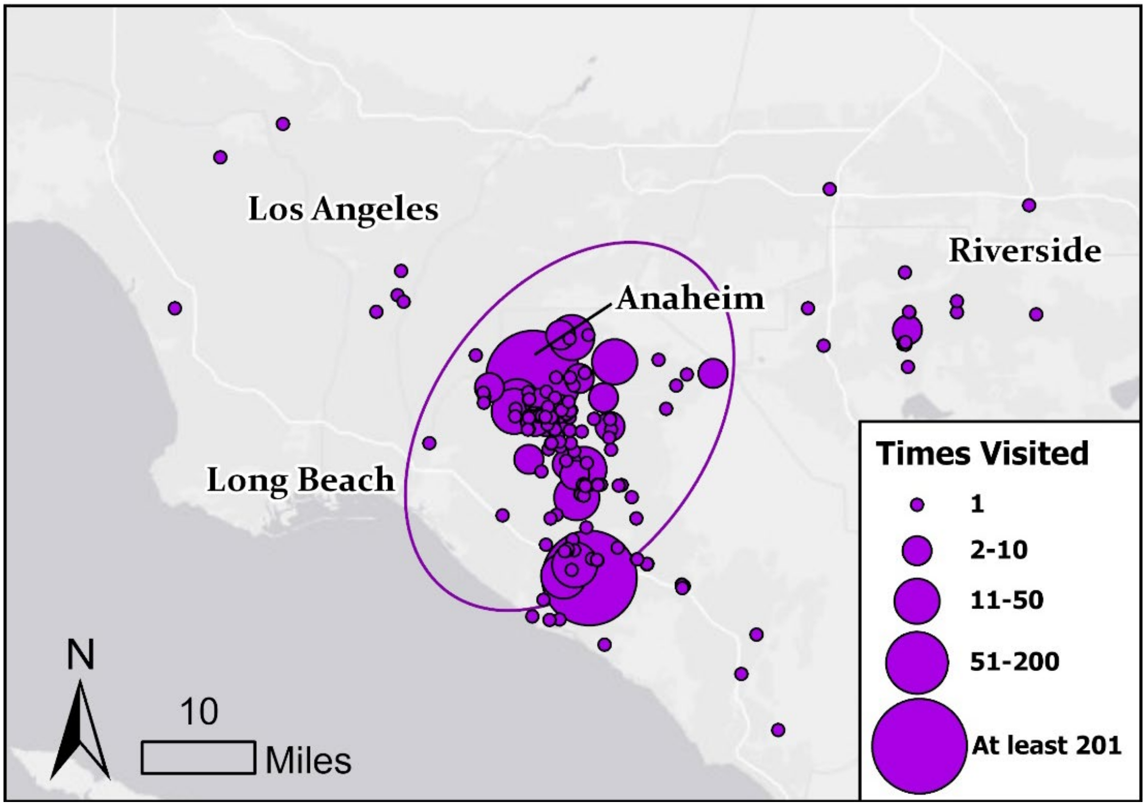


Figure 16. Trip destinations of Tesla Model S-60_80

Analysis of vehicles SDE activity spaces show that longer-range BEVs (particularly Tesla Model S vehicles) are also used to travel frequently over a much wider area and potentially a much larger range of opportunities than shorter-range BEVs. The results of the SDE analysis are plotted against annual VMT in **Figure 17**, with a logarithmic scale on the vertical axis. Vehicles with larger SDEs are used to visit destinations spread over a much larger area. As the slight upward trend in the plot shows, vehicles that travel more miles per year generally cover a larger area, but longer-range BEVs, particularly Teslas, have larger SDEs than other BEVs with similar annual VMTs. The several Teslas and one Bolt-60 with SDEs larger than 3,000 square miles were used to travel over an area more than an order of magnitude larger than the most wide-ranging Leafs.

Table 11. Summary statistics for area of Standard Deviation Ellipse area activity space by vehicle type

Vehicle Type	Minimum (mi^2)	25th percentile (mi^2)	Median (mi^2)	75th percentile (mi^2)	Maximum (mi^2)
Leaf-24	4	15	32	70	335
Leaf-30	9	27	46	144	357
RAV4 EV-42	17	33	42	71	88
Bolt-60	19	58	101	155	2,941
Model S-60_80	33	221	341	866	6,870
Model S-80_100	62	164	487	1,624	5,100

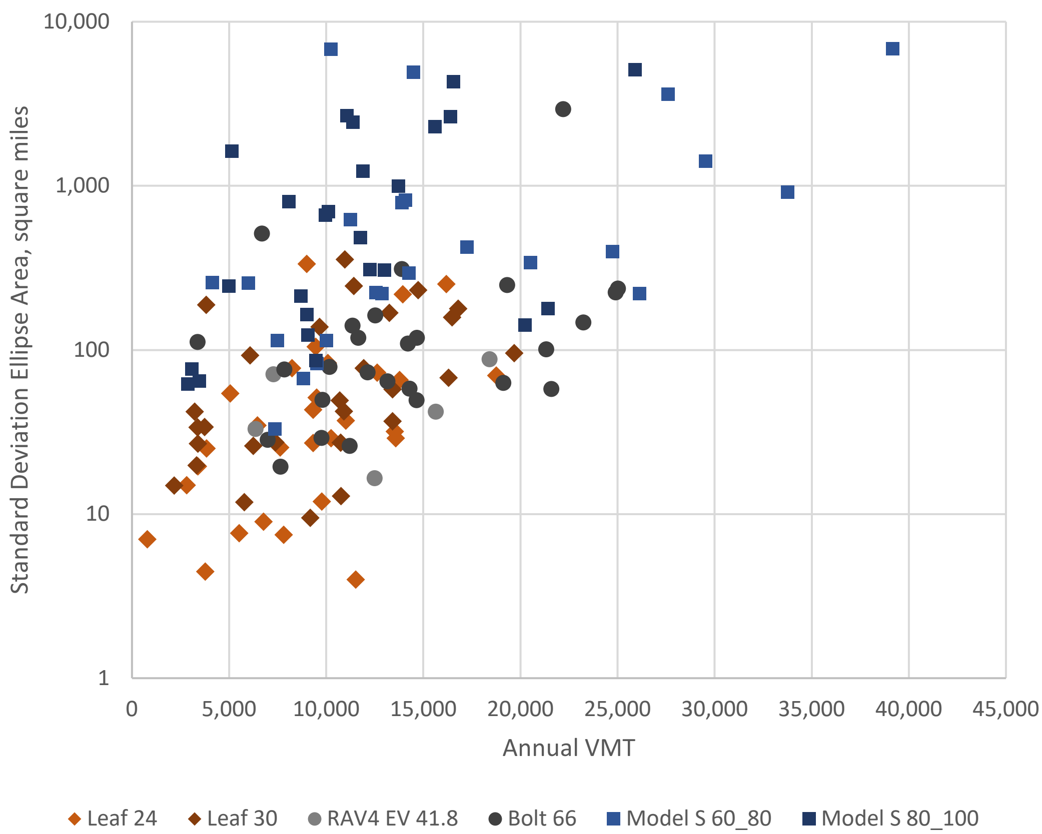


Figure 17. Area of standard deviation ellipse of vehicle destinations plotted against annual VMT

Table 11 identifies quartiles of SDE areas for the six vehicle types and shows that almost all the Tesla Model S traveled over a wider area than the median Leaf. In addition, the median Tesla traveled over a wider area than any Leaf. As is the case with the analysis of destinations, the activity spaces of Bolt-60 drivers are roughly halfway between those of Leaf and Tesla drivers, despite their vehicles having as much range as many of the Tesla Model S, perhaps due to differences in access to chargers away from home.

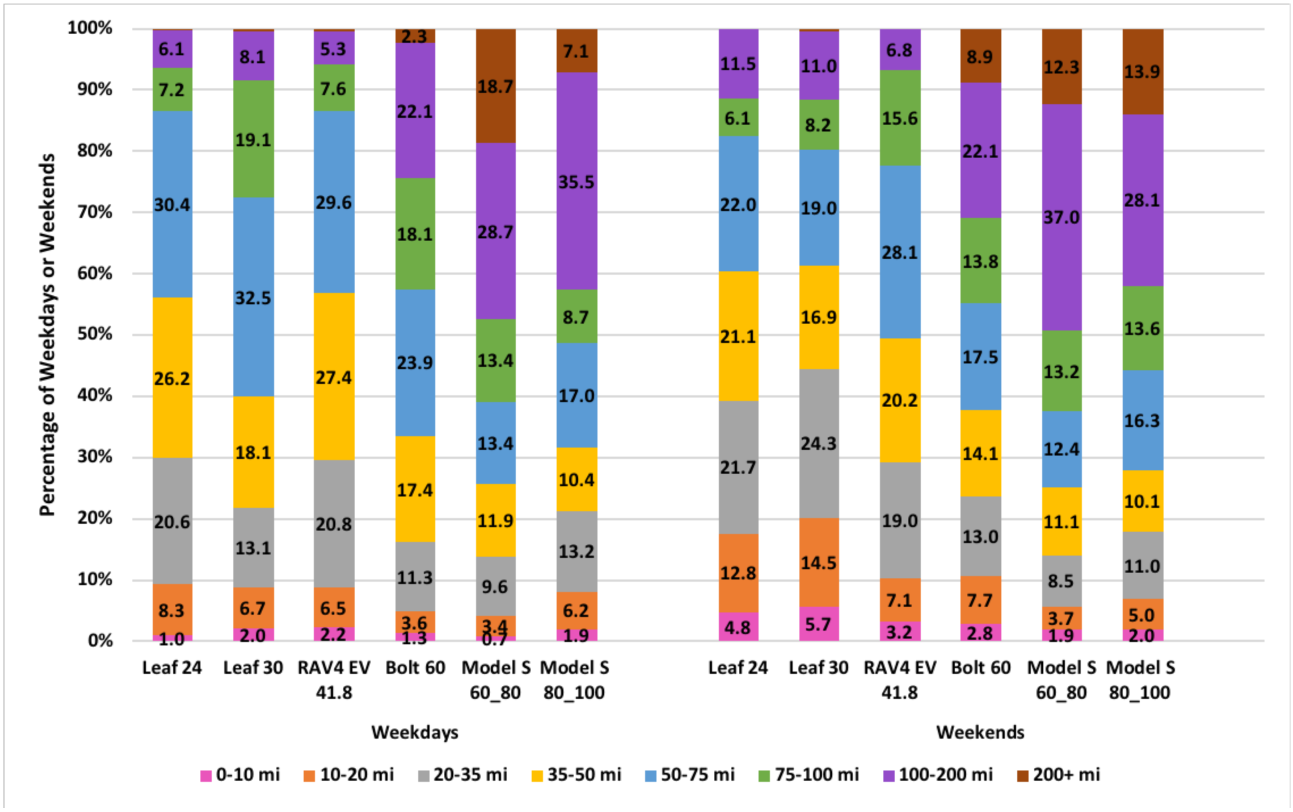


Figure 18. Percentage of Daily VMT by Distance Bins: Weekdays vs. Weekends

Figure 18 shows the share of weekdays and share of weekends when the BEV was driven, binned by daily VMT. For all BEV models, the percentage of days with trips that were 10 miles or less was higher on the weekends than on weekdays. The Leaf-24, Leaf-30, RAV4 EV-42 and Tesla Model S-60_80 had a higher percentage of days with trips that were 100 to 200 miles on weekends than on weekdays.

Using the criteria for 50 miles or more to define Long Distance Travel (LDT)(BTS 2017) days, **Figure 19** shows the share of VMT accomplished on these days as a percentage of the total VMT. A given point on one of the six box and whisker plots denotes the average share of LDT VMT for a specific vehicle, belonging to the vehicle model category represented by that box plot. The box outlines the range of data between the first and third quartile. VMT on LDT days accounted for an average of 52% of the total VMT for all BEVs, and 36.1%, 44.7%, 40.0% and 57.3% for the Leaf-24, Leaf-30, RAV4 EV-42, and Bolt-60, respectively. Both the Tesla Model S-60_80 (65.9%) and Tesla Model S-80_100 (64.8%) have almost two-thirds of their VMT accomplished on LDT days, perhaps indicating that long-range BEVs are more often used for long-distance travel rather than regular weekday commuting.

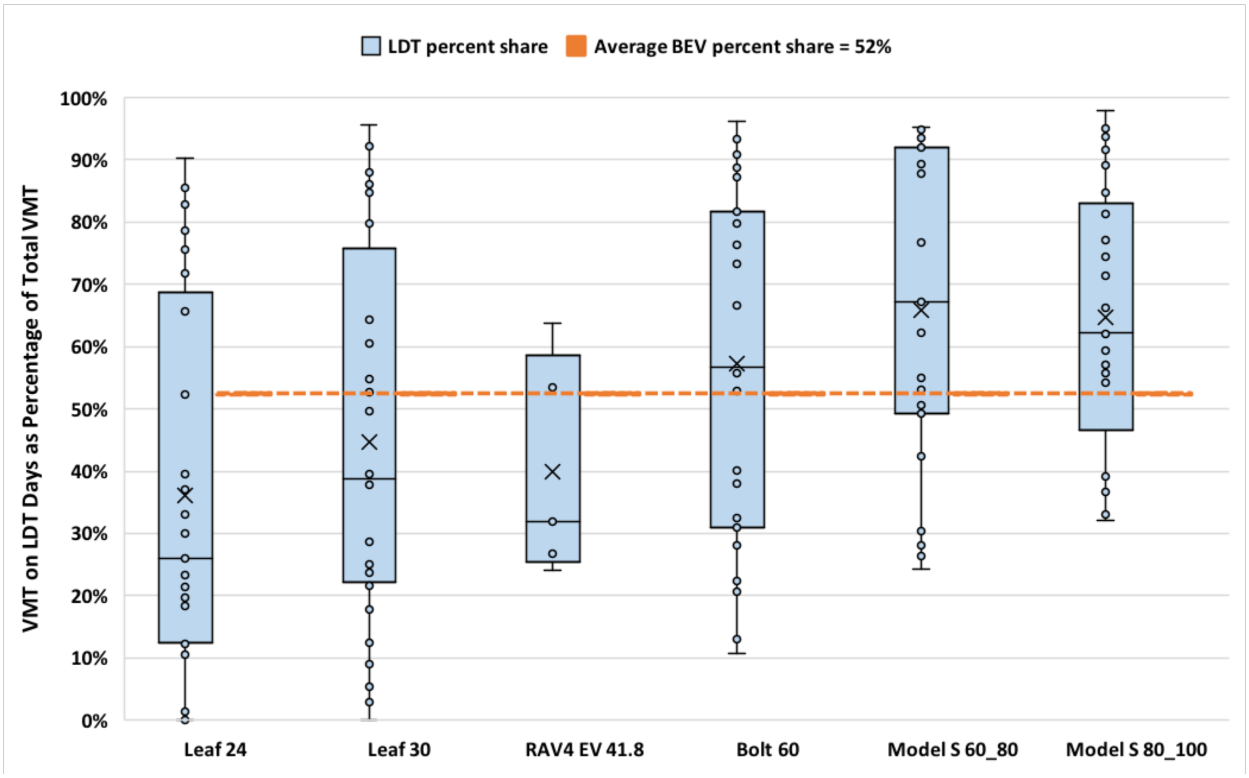


Figure 19. Share of VMT on LDT (50 miles or more) as Percentage of Total VMT by BEV Type[2]

3.3 PEVs Used for Commuting

Figure 20 below shows share of PEVs by type that were used by HH members working fulltime for commuting purposes and non-commuting purposes across all the HHs in which logger data was used. Overall, about 70% of each vehicle type was used for commuting, except for the Chrysler Pacifica-16 where only 50% were used for commuting. This could be attributed to the fact that the Chrysler Pacifica-16 was the only minivan in our sample and the rest of the vehicles were all sedans.

[2] The whiskers, or lines connected to the box, illustrate the range between the minimum value and first quartile as well as the range between the third quartile and the maximum value. The line intersecting the box denotes the median value and the cross shows the average value.

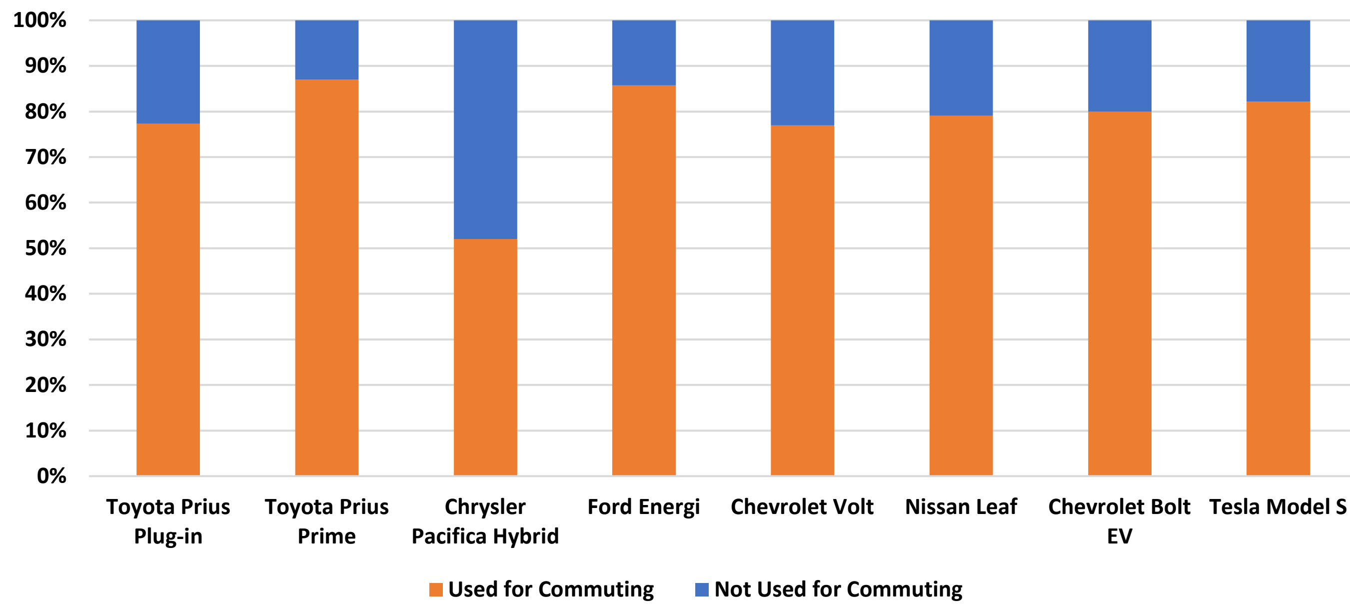


Figure 20. Number of PEVs Used for Commute Purposes by Type.

3.4 Battery Electric Vehicle Charging

Descriptive summaries and analyses depicted in **Figure 21- Figure 33** are based on the data collected from the loggers. BEV charging summary statistics are presented in **Table 12**. **Figure 21** shows the probability that the BEV charges on a given day within the duration for which it was logged, called the logging window. **Figure 22** and **Figure 23**, respectively, depict the percent share of charging sessions and charged kWh by charging level.

Table 12 summarizes the key charging related information of the BEVs. When we consider only the days when the BEV charged, the Bolt-60 had a comparable number of charging sessions per day, as did the Leaf-24 and Model S-60_80. However, when we include the days on which the BEV did not charge, as may be expected, the Model S-60_80 and Model S-80_100 had fewer charging sessions per day than the Leaf-24 and Leaf-30, respectively. The Bolt-60 had the longest average charging duration per day, whereas the RAV4 EV-42 had the lowest.

Table 12. Charging Summaries on by BEV Type

Within the Logging Window Including Days When BEV Did not Charge	BEV	Average Sessions/Day	Average DCFC Sessions/Day	Average L1/L2 Sessions/Day	Average kWh/Day	Average Duration/Day (minutes)	Average VMT/Day (miles)
	Leaf-24	0.9	0.0	0.8	5.8	196.0	27.2
	Leaf-30	0.7	0.1	0.6	6.7	138.2	28.8
	RAV4 EV-42	0.8	0.0	0.8	10.5	106.3	31.7
	Bolt-60	0.8	0.0	0.8	10.1	246.2	38.6
	Model S-60_80	0.8	0.1	0.7	17.6	160.1	47.3
	Model S-80_100	0.6	0.1	0.5	13.3	108.6	35.1

On Days When the BEV Charged	BEV	Average Sessions/Day	Average DCFC Sessions/Day	Average L1/L2 Sessions/Day	Average kWh/Day	Average Duration/Day (minutes)	Average VMT/Day (miles)
	Leaf-24	1.4	0.1	1.3	9.0	306.9	36.4
	Leaf-30	1.3	0.3	1.0	12.1	247.9	43.3
	RAV4 EV-42	1.2	0.0	1.2	15.8	159.2	39.2
	Bolt-60	1.7	0.0	1.7	20.5	499.1	53.4
	Model S-60_80	1.4	0.2	1.2	28.0	254.6	62.9
	Model S-80_100	1.3	0.2	1.1	27.7	159.2	56.4

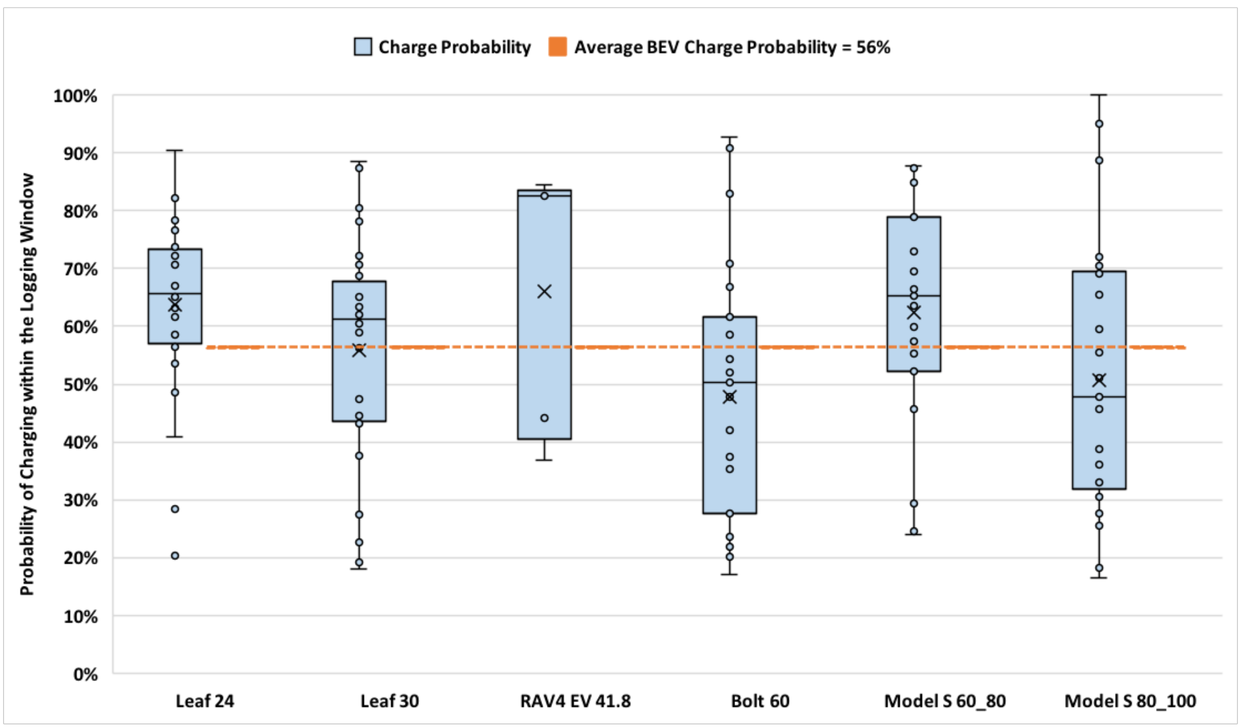


Figure 21. Probability of Charging Within the Logging Window of Individual BEVs by BEV Type

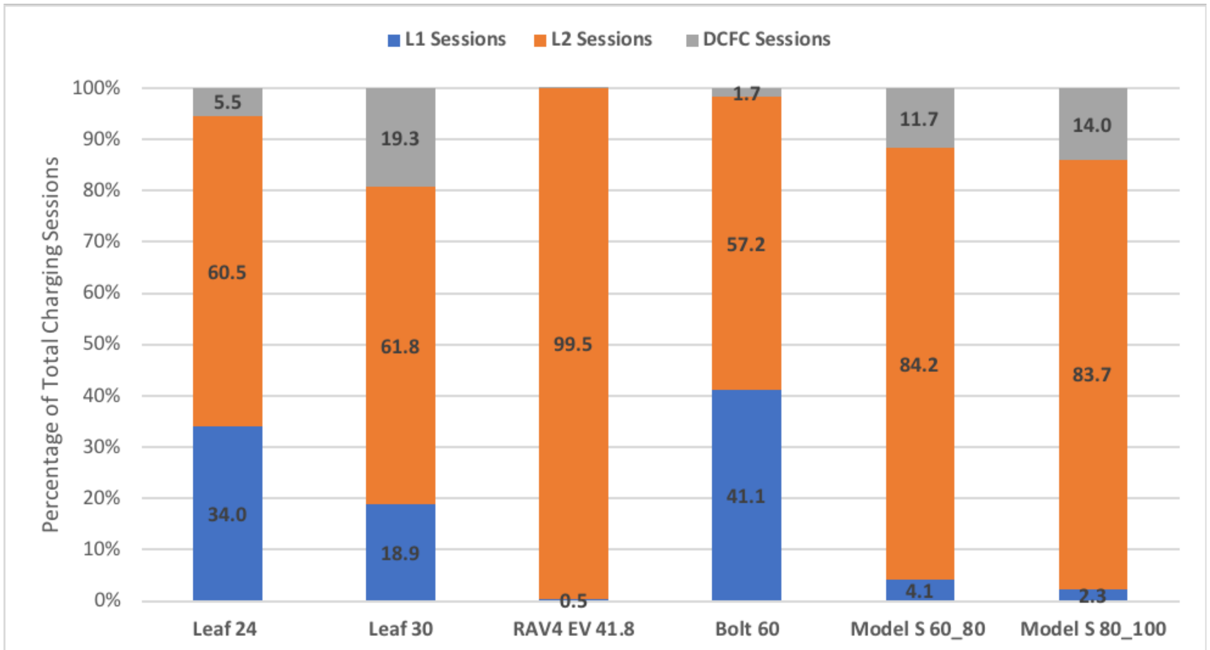


Figure 22. Share of Charging Sessions by Charging Level and BEV Type

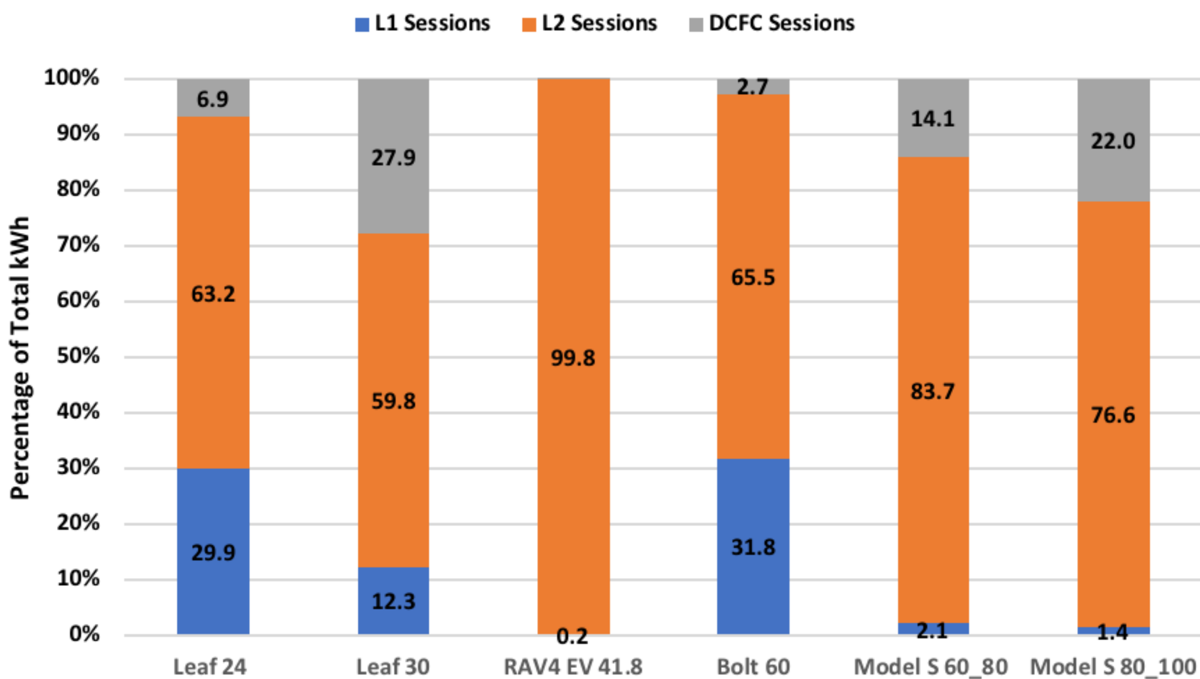


Figure 23. Share of Charging kWh by Charging Level and BEV Type

Out of the 36,921 charging sessions in total, 22% were at L1, 69% were at L2, and 9% were DCFC sessions. L2 charging accounted for most charging sessions and charged kWh for all the BEV types. Leaf-30 had the highest share of DCFC sessions and the highest share of charged kWh from DCFC charging. DCFC charging sessions by Leaf-30 accounted for close to 40% of all the DCFC charging sessions, followed by Model S-60_80 and Model S-80_100, which respectively accounted for 23% and 20% of all the DCFC charging sessions. **Figure 24** shows the percent of charging sessions (all charging levels combined) by start time (hourly intervals) on weekdays and weekends. There was a noticeable weekday peak around 8 am, which can be attributed to charging at work, and the 11 pm-1am window on weekdays, which is typical of home charging. On the weekends, the highest percentage of charging sessions occur during the 11pm-1am window, followed by 9 pm and 7 pm. Since the RAV4 EV-42 had only a few L1 sessions and is not DCFC compatible, it has been omitted from the charging session starting time, charger utilization, charging session starting and charged SOC plots (**Figure 25**, **Figure 27**, **Figure 29**, **Figure 31**, **Figure 32**).

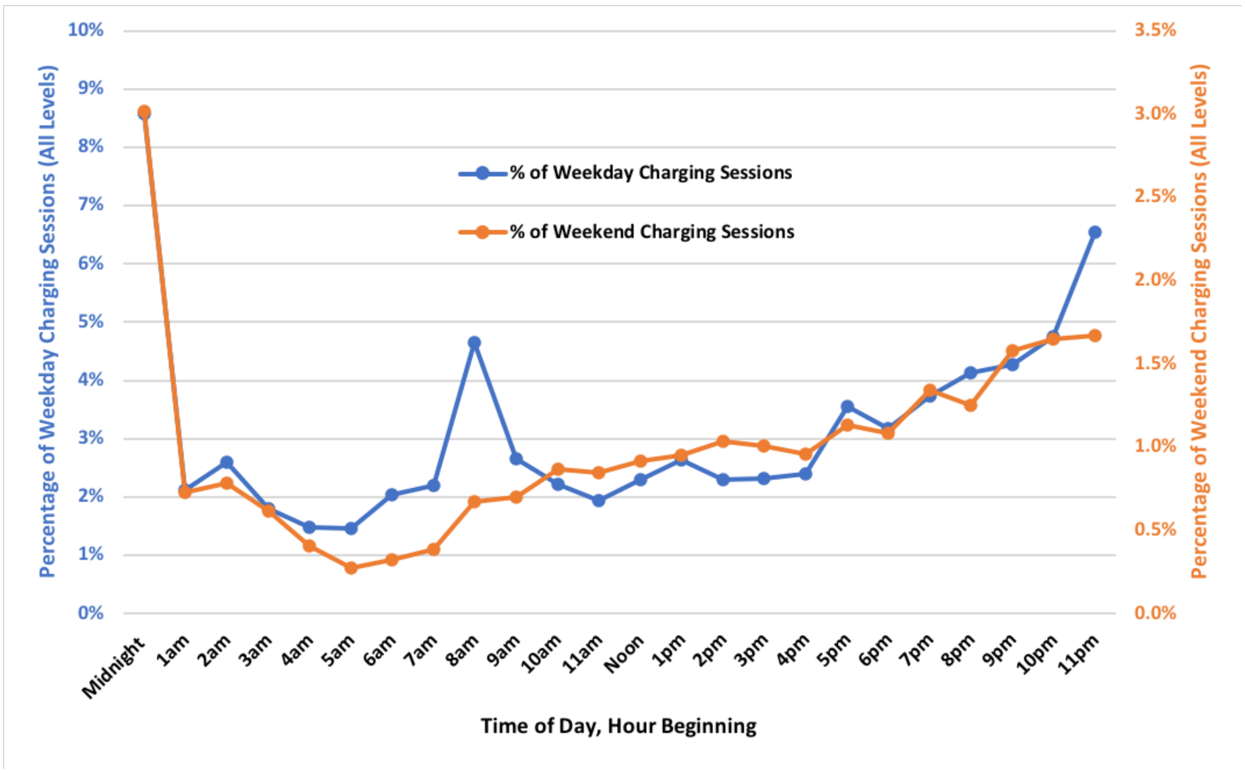


Figure 24. Charging Session Starting Time: Weekdays vs. Weekends (all BEVs and all charging levels)

Figure 25-**Figure 27** show the results of a closer inspection of the charging session start time by charging level (L1, L2, and DCFC). For all BEV types, most of the highest percentages of L1 Sessions were between 2pm and 11pm. The peak in L1 charging session start time was around 9pm for Leaf-30 and around 11pm for the Leaf-24, respectively. Across all BEV types, the highest percent of L2 sessions started around or after 11pm. There was a noticeable spike in the share of L2 charging sessions for all BEVs starting at around 8am, perhaps indicative of access to L2 charging away from home. Another noticeable spike in the share of L2 charging sessions was for the RAV4 EV-42 at 3am. Not all BEV drivers use DCFC on our study as 3 Bolt-60 and 5 NIssan Leaf havn't had DCFC capabilties but 22 Bolts-60, 13 Leaf-24s, 5 Leaf-30s, and 1 Model S-80_100 did not use it even once on the logging period. An interesting observation with respect to DCFC charging was the noticeable peak in DCFC charging session start times of the Leaf-30 at 5am. This time window could potentially reflect the preference of Leaf-30 owners to stop and use DCFC charging on their commutes. The peak DCFC sessions were 9am and noon for Bolt-60, 8am and 6pm for both the Model S-60_80 and Model S-80_100, and 11am and 2pm for the Leaf-24.

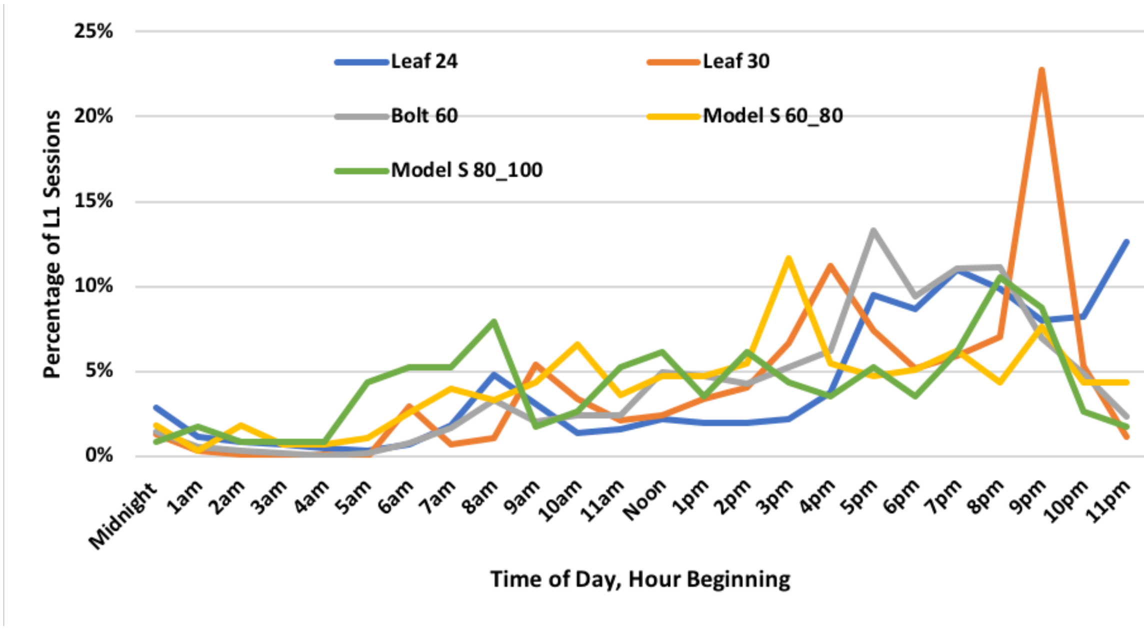


Figure 25. Percentage of L1 Charging Start Times by Time of Day and BEV Type (RAV4 EV-42 is excluded from this dataset, as it was very rarely charged on an L1 charger)

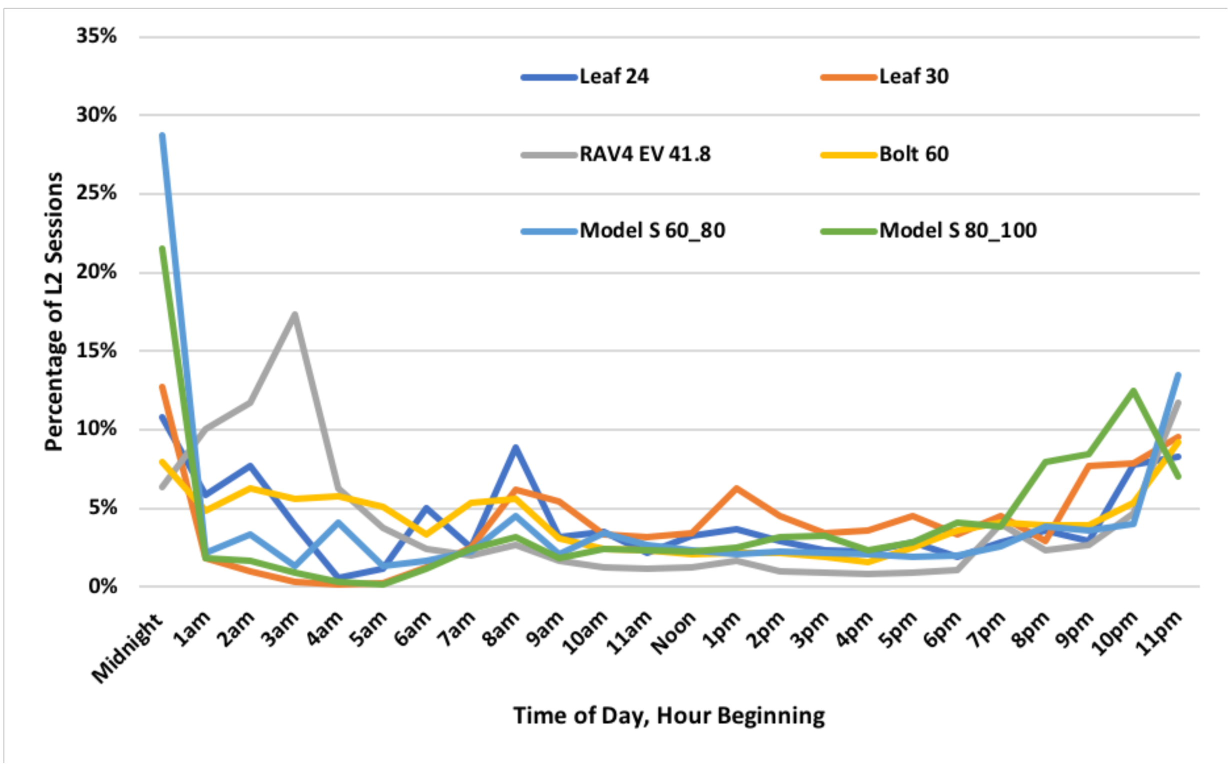


Figure 26. Percentage of L2 Charging Start Times by Time of Day and BEV Type

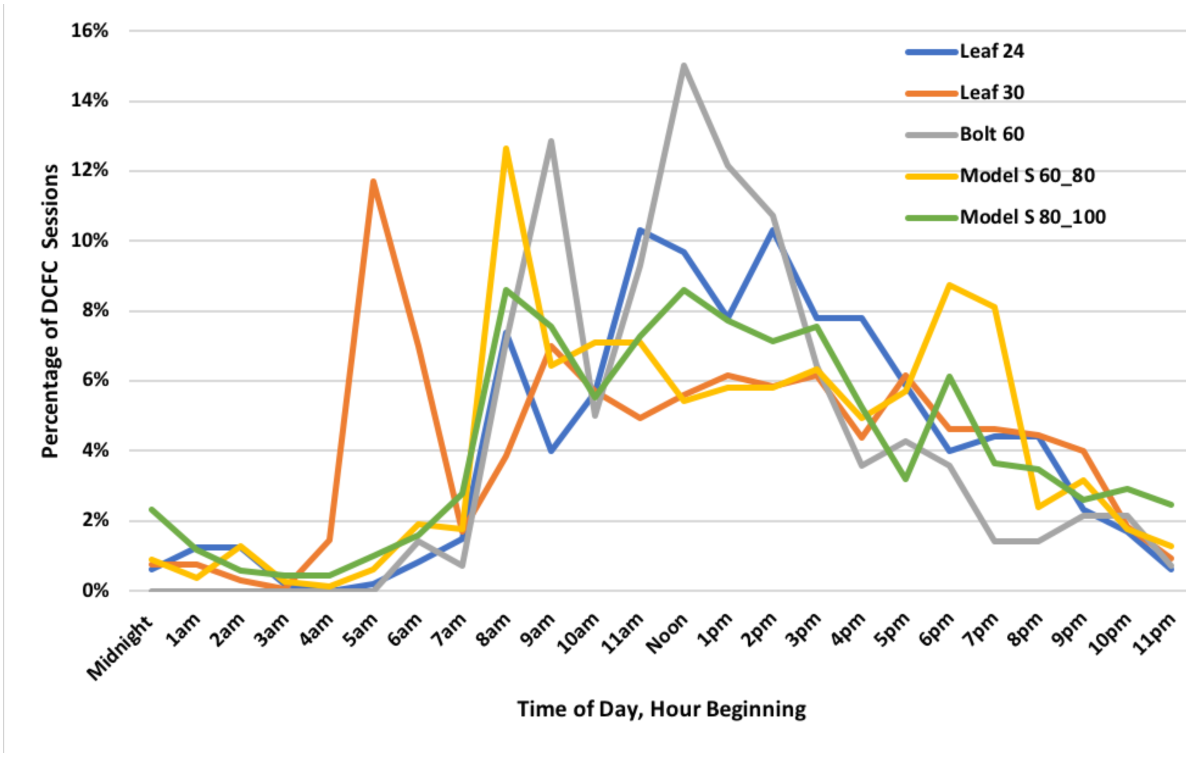
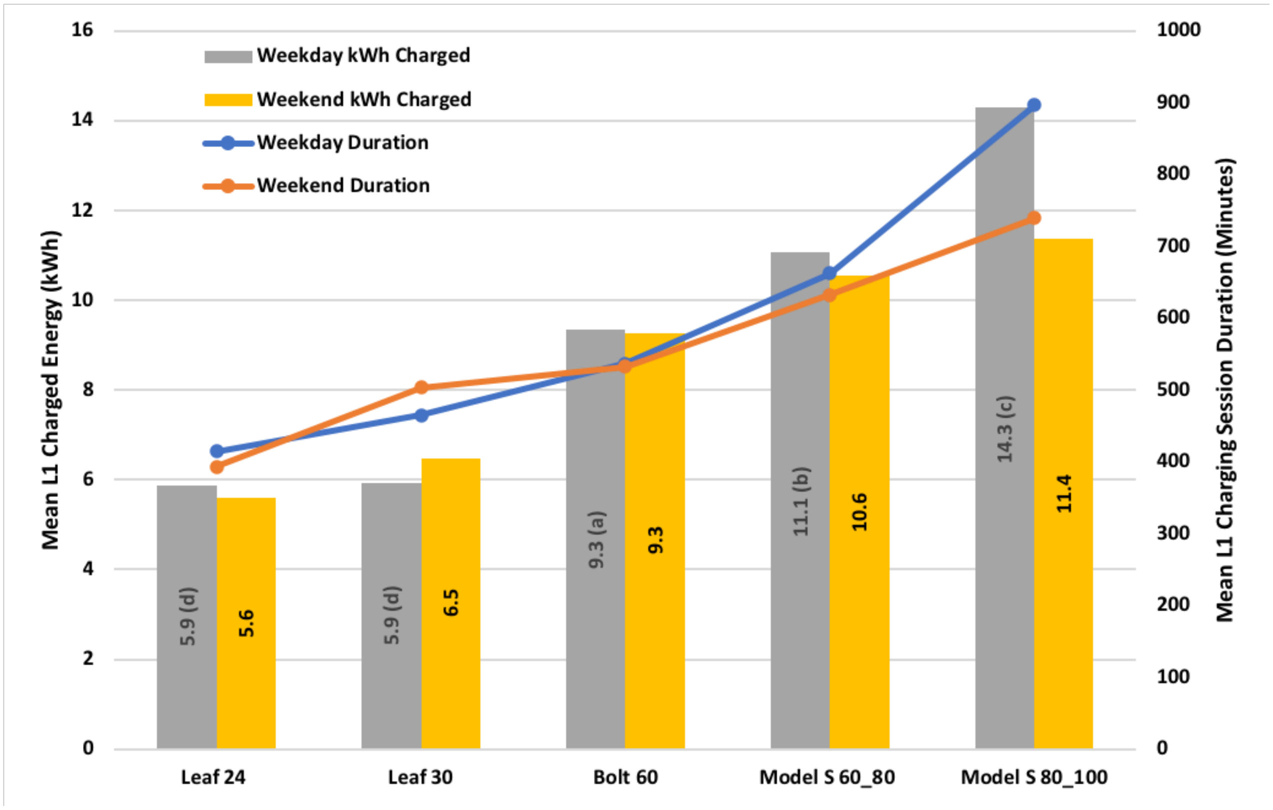


Figure 27. Percentage of DCFC Charging Start Times by Time of Day and BEV Type (RAV4 EV-42 is excluded from this dataset, as it cannot be charged on a DCFC)

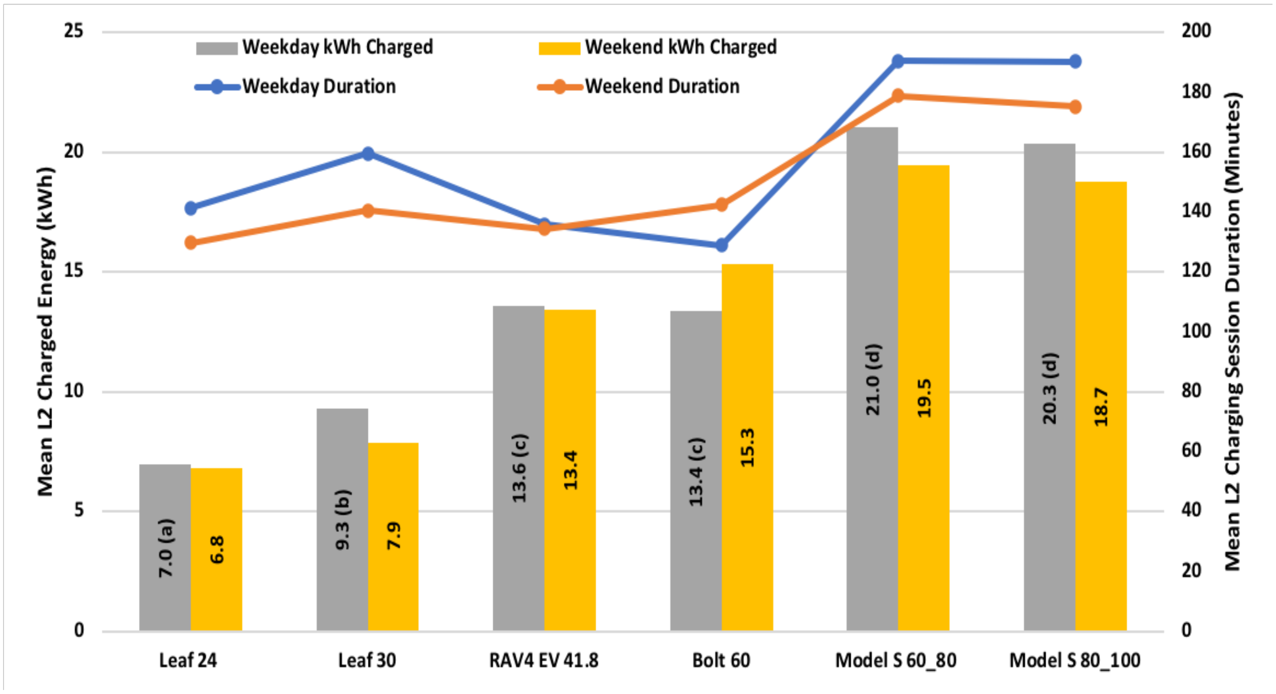
Figure 28-**Figure 30** show the average charging session duration and average kWh charged by charger level. For L1 charging, the Leaf-30, on average, had higher charging energy per session and longer charging session duration on weekends than on weekdays. The Bolt-60, on average, had similar charging energy per session and similar charging session duration on weekends and on weekdays when using L1 charging. On average, the Leaf-24, Model S-60_80, and Model S-80_100 all had lower L1 charging energy per session and shorter L1 charging session duration on weekends than on weekdays. When using L2 charging, all BEV models, except the Bolt-60 and RAV4 EV-42, on average, had lower charging energy per session and shorter charging session duration on weekends than on weekdays. The Bolt-60 had higher average charging energy per session and longer average charging session duration on weekends than on weekdays, when using L2 charging. The RAV4 EV-42 had similar average L2 charging energy per session and similar average L2 charging session duration on weekends and on weekdays.

The average charging session duration and average amount of charge per session on DCFCs were similar between the weekdays and weekends for the Leaf-30, but greater on weekends than on weekdays for the Bolt-60, Model S-60_80, and Model S-80_100 (**Figure 30**). On the other hand, a vehicle with a large battery size, the Leaf-24, had shorter average charging session duration and less average charge per session on weekends than on weekdays.



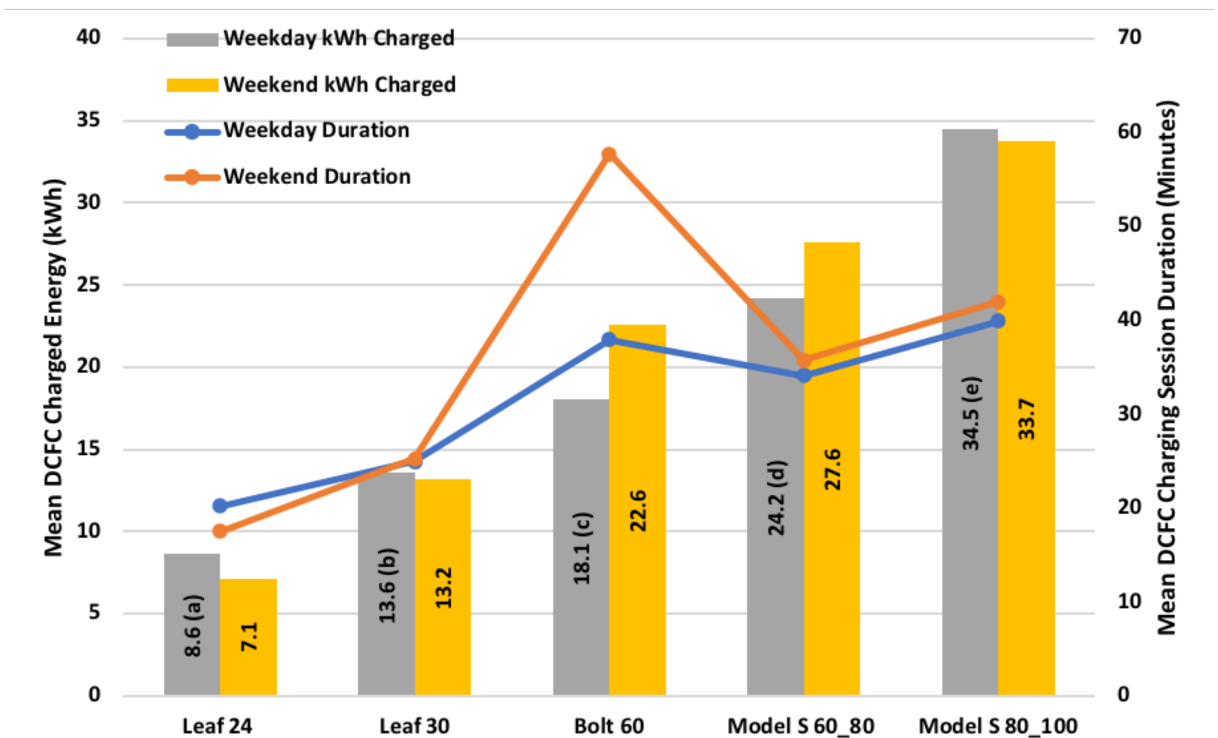
*If two vehicle models' weekday kWh charged energy means do not share a letter, they are significantly different.

Figure 28. Average L1 Charging kWh Charged and Charging Duration: Weekdays vs Weekends (RAV4 EV-42 is excluded from this dataset, as it was very rarely charged on an L1 charger)



*If two models' weekday kWh charged means do not share a letter, they are significantly different.

Figure 29. Average L2 Charging kWh Charged and Charging Duration: Weekdays vs Weekends



*If two vehicle models' weekday kWh charged energy means do not share a letter, they are significantly different.

Figure 30. Average DCFC Charging kWh and Duration: Weekdays vs Weekends

Figure 31-Figure 33 show the average charging session starting and ending battery SOC by charger level on weekdays and on weekends. When using L2 charging, the Leaf-30 compared to the other BEV types had the lowest average starting SOC on weekdays, but when using L1 charging, it had the second highest average starting SOC on weekdays. The Bolt-60, compared to all other BEV types, had the lowest average charged SOC when using L1 charging on weekdays, L1 charging on weekends, and when using L2 or DCFC charging on weekdays. The Bolt-60 also had the highest average starting SOC when using L1 or L2 charging on weekdays and on weekends. When using DCFCs, the Leaf-30 average starting SOC on weekdays was the lowest and its charged SOC on weekdays and on weekends was the highest. Overall, for short-range BEVs (Leaf-24 and Leaf-30), the charging session ending SOC was around 90% or more on weekdays and on weekends when using L1 or L2 charging. In addition, the Leaf-30 average charging session ending SOC was highest (90% or more) when using DCFCs on weekdays and on weekends. The Model S-60_80 and Model S-80_100 started their L2 charging sessions on weekdays and on weekends at higher SOCs compared to the short-range BEVs (Leaf-24 and Leaf-30).

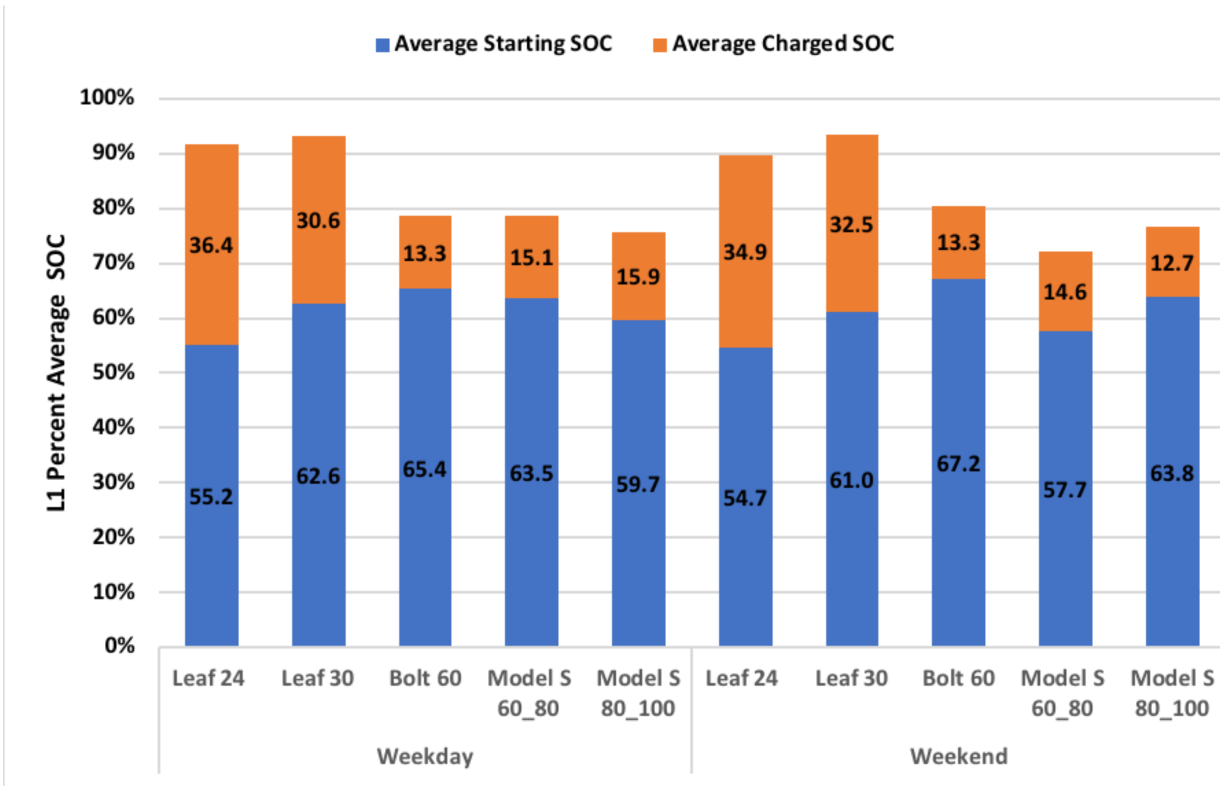


Figure 31. L1 Charging: Average Starting and Charged SOC

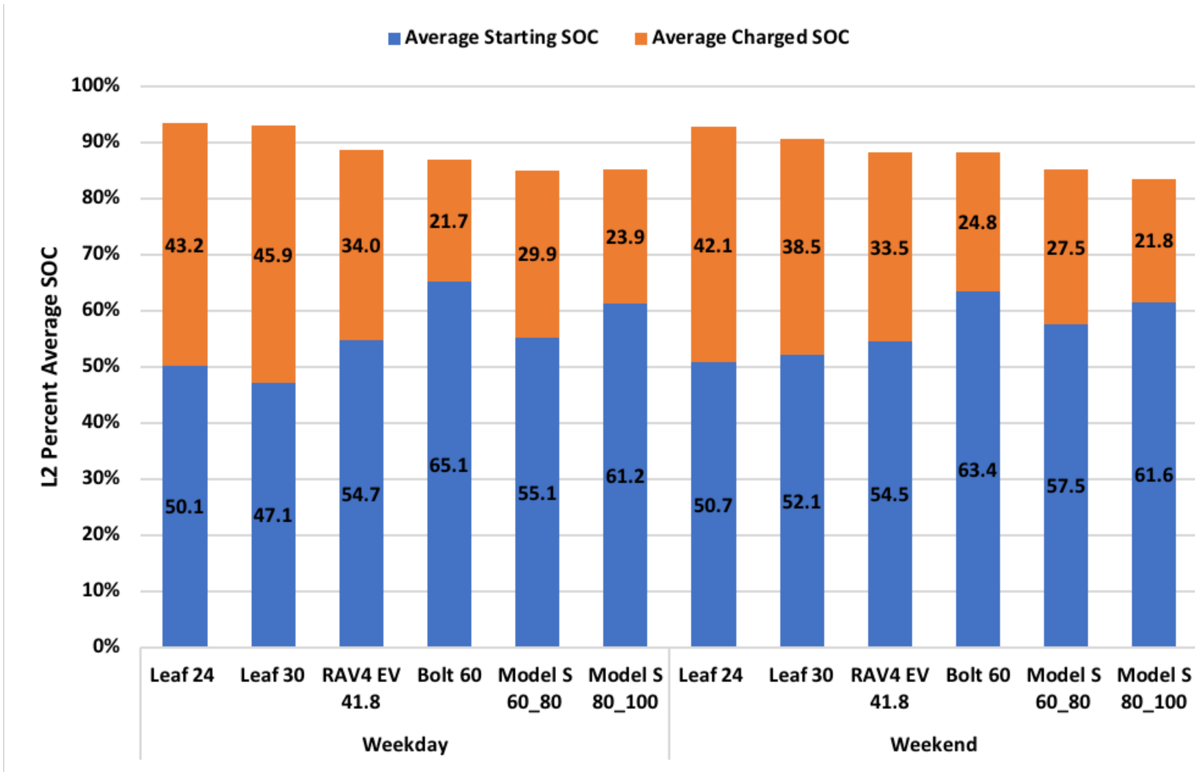


Figure 32. L2 Charging: Average Starting and Charged SOC

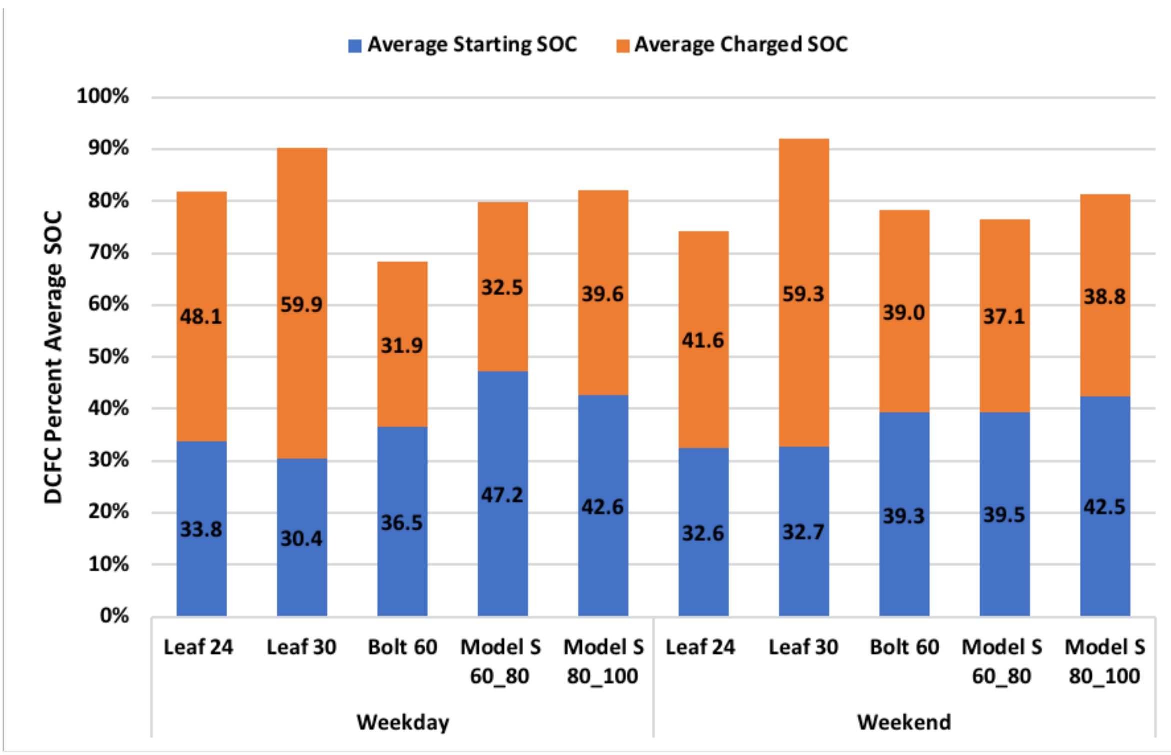


Figure 33. DCFC: Average Starting and Charged SOC

3.5 Plug-in Hybrid Electric Vehicles (PHEVs) Driving

Results presented in **Table 13** and depicted in **Figure 34**-**Figure 44** in this section are based on the data collected from the loggers. In this section, we present the vehicle level analysis of the PHEVs. We used the methods presented in Section 2.5 to estimate the trip level distribution of electric vehicle miles travelled (eVMT), gasoline vehicle miles travelled (gVMT), and the total energy consumption per trip, reported in gallons of gas and kWh of electricity used. We also compare the different PHEVs in terms of their utility factor (UF), which is the ratio of the charge depleting range to the distance travelled (SAE 2010). Compared to BEVs, which have only one source of propulsive power, estimating the eVMT of PHEVs is not as straightforward since the PHEVs have three driving modes: Charge Sustaining (CS), Charge Depleting Blended (CDB), and All Electric (AE) or Zero Emission (ZE) modes. In the CS mode, a PHEV is driven like a regular hybrid electric vehicle using only gasoline. When the PHEV is driven in ZE mode, the engine is never turned on and only electricity is consumed, whereas in the CDB mode, both gasoline and electricity are consumed.

Table 13. PHEV VMT, eVMT, gVMT, Fuel and Energy Consumption by PHEV Type

PHEV Type	Total eVMT (miles)	Total gVMT (miles)	Total VMT (miles)	Total Gasoline Consumed (Gallons)	Total Charging Energy(kWh)
Prius Plug-in-4.4	46106	268125	314231	5528	17774
C-Max/Fusion-7.6	249868	476501	726389	11800	77174
Prius Prime-8.8	142209	184477	336465	3593	29948
Pacifica-16	137049	123153	272970	4131	70301
Volt-16	361704	204650	566354	5947	99949
Volt-18	313926	145331	459257	3952	83621
All PHEVs	1250863	1402236	2675665	34951	378767

Table 13 provides an overview of the PHEV driving and charging data considered in the vehicle level analysis. **Table 13** shows the total eVMT, total miles travelled on gasoline (gVMT), and total PHEV VMT for the individual PHEVs by type.

Figure 35 shows the average utility factor UF by PHEV type. On average, the Volt-18 had the highest UF, followed by the Volt-16. The UF of the C-Max/Fusion PHEV was half that of the Volt-18. The UF measured in our project is different than that used for current policies and regulations. Current regulations are based on a UF standardized in the SAE J2841 (SAE 2010) that is based on daily miles from travel surveys and the assumption that each vehicle starts the travel day fully charged. Our sample suggests that not all PHEVs are charged every day and that different PHEVs charge differently. Furthermore, we did not install loggers in vehicles that were used as hybrids or charged less than 4 times per month. Based on the project survey, 4% of the Chrysler Pacifica-16, 5.9% of Volt owners, 9% of the Toyota Prius Prime-8.8, 16.5% of the Ford Energi owners, and 18.5% of the Prius Plug-in-4.4 owners drove mostly on gas and were not accumulating eVMT. We believe that these figures underestimate the phenomena because of a selection bias, where users who do not plug in their cars are less likely to take and finish a survey on the topic. **Figure 36** shows the UF for each of the vehicles based on the SAE2841 standard, the actual eVMT and VMT measured, and the utility factor adjusted to the survey results, including the vehicles with utility factor of zero. For all vehicles, except the Volt-16, we measured lower UFs than the SAE standard. For instance, the logged Prius PHEVs achieve only 62% of the expected UF or 48% when accounting for users who are not plugging in. For the longer-range Volts, we measured UFs that were closer to the values determined by the SAE2841.

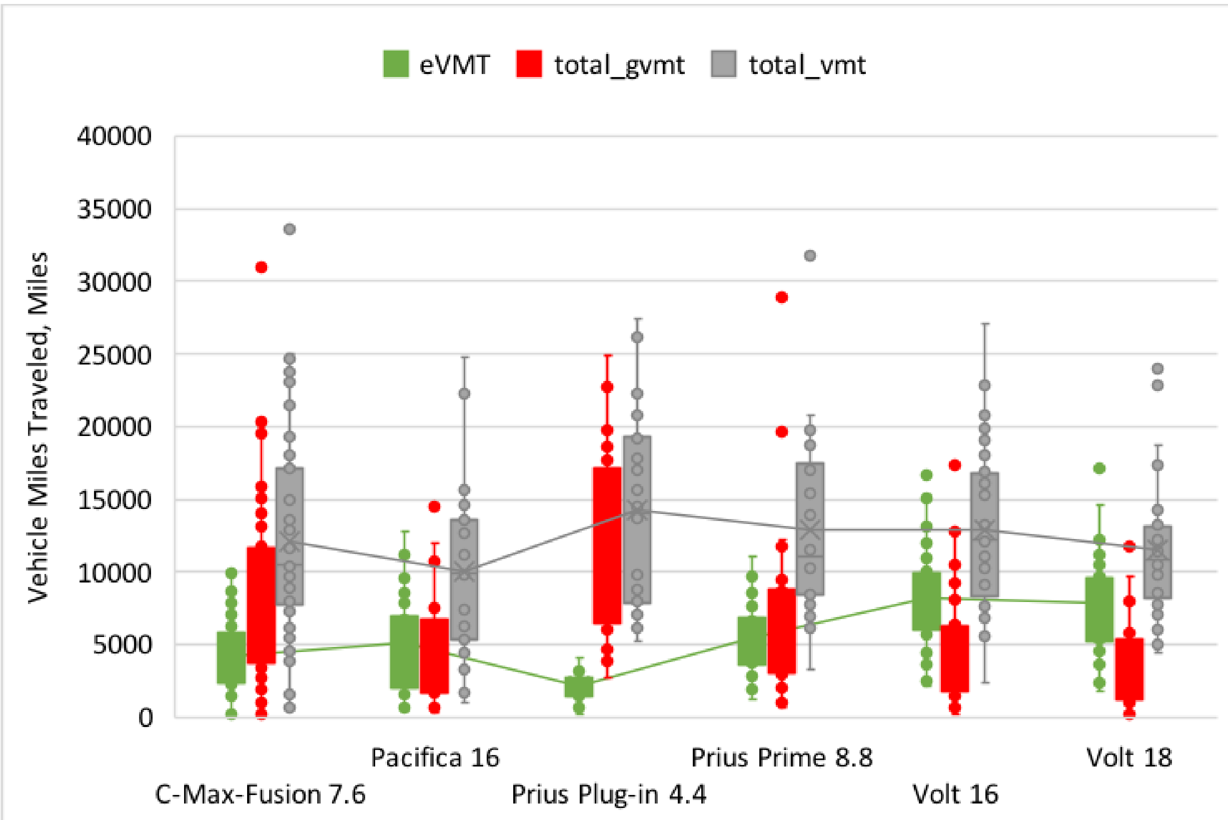


Figure 34. PHEV eVMT, gVMT, and VMT of Individual PHEVs by PHEV Type

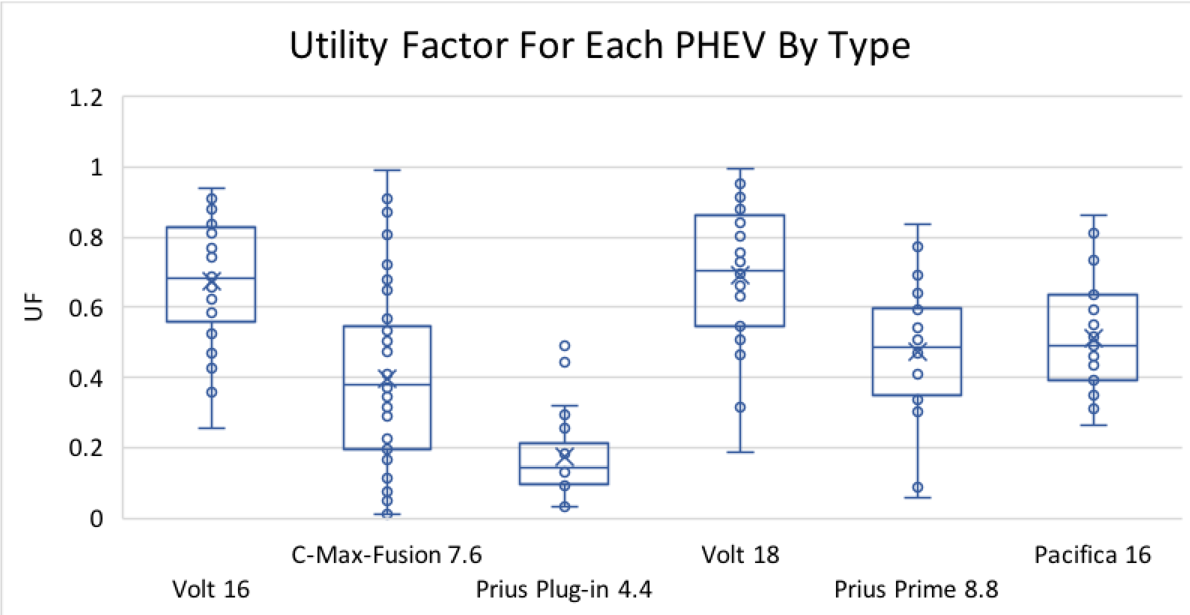


Figure 35. Utility Factor (UF) for Each PHEV by Type

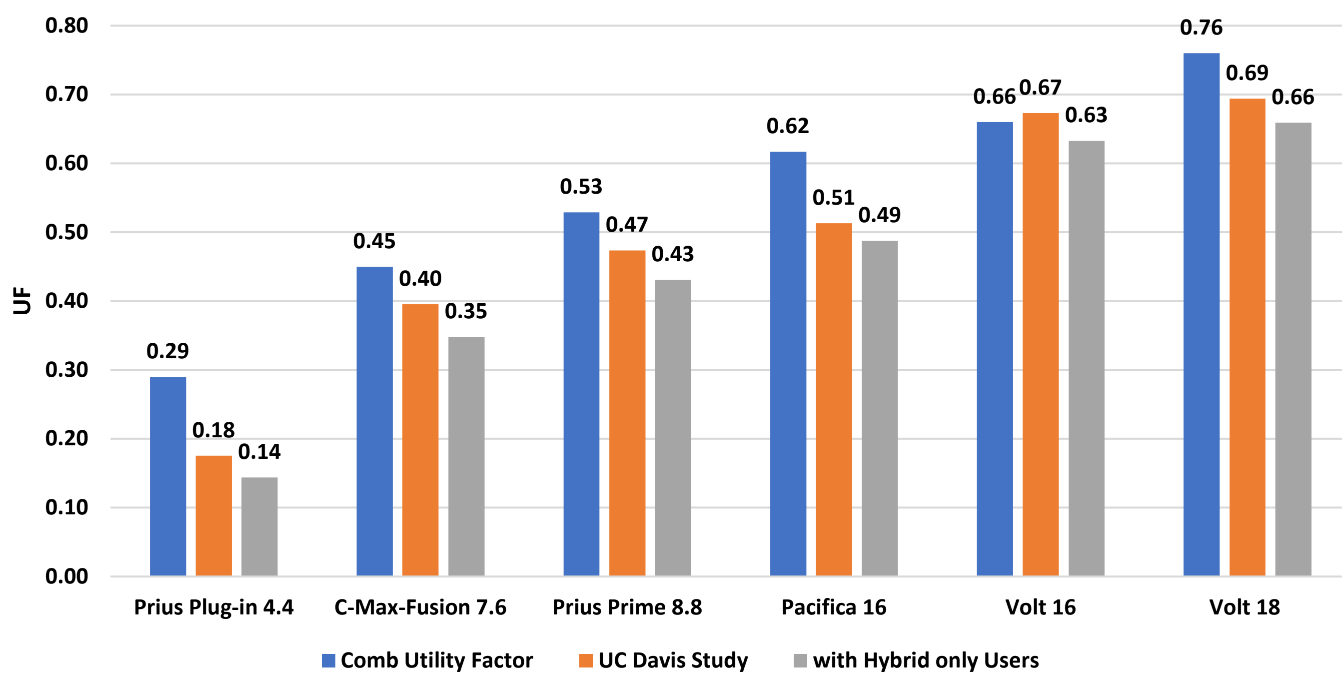


Figure 36. Average UF by PHEV Type

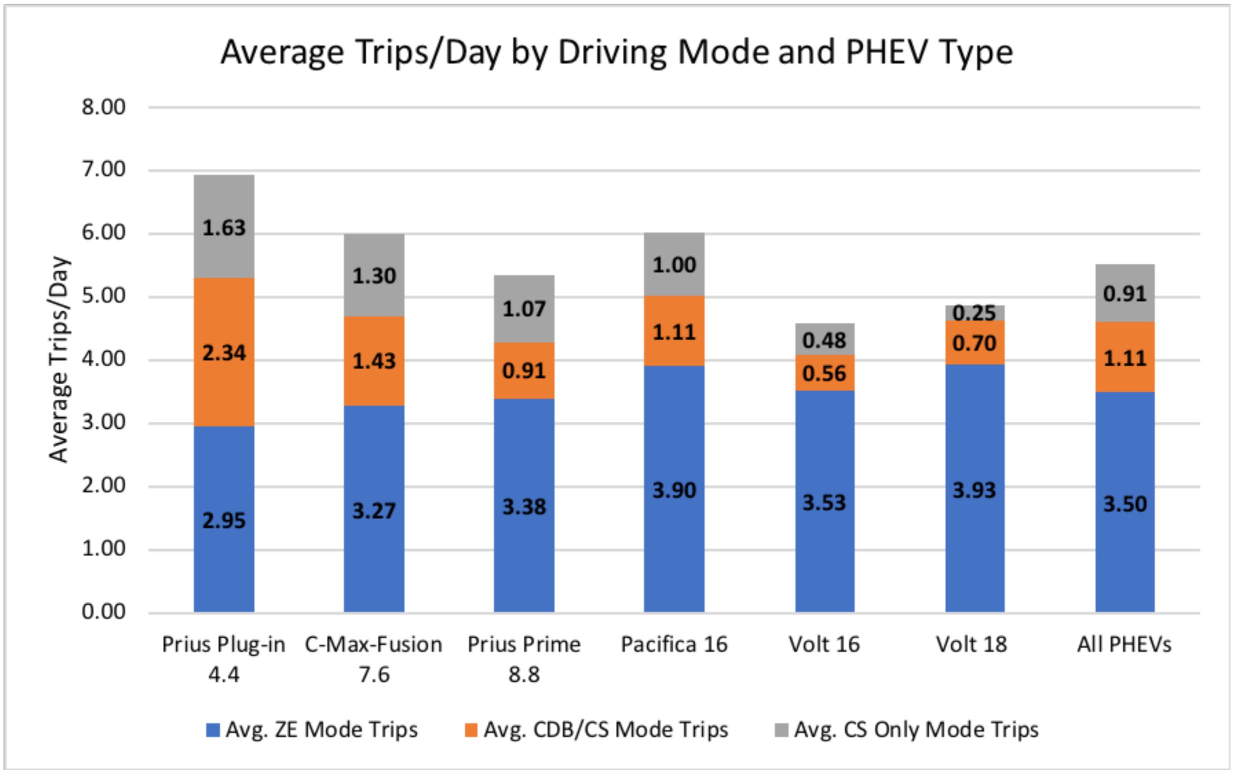


Figure 37. Average Trips per Day by Driving Mode

As shown in **Figure 37**, At the day level, on average, the Prius Plug-in-4.4 was driven approximately 7 trips per day, the C-Max/Fusion-7.6 and Pacifica-16 were driven approximately 6 trips per day, and the Volt-16, appoximately 5.5 trips per day. The Volt-16, Volt-18, and Prius-Prime-8.8 had fewer average daily trips than the PHEV fleet (5.52 trips/day). On average, when compared to other PHEVs, the Volt-18 had the greatest share of trips accomplished on electricity alone (ZE only mode), also referred to as zero emission trips. The Volt-18 also had the lowest share of trips that were accomplished on gasoline alone in the charge sustaining mode (CS only mode).

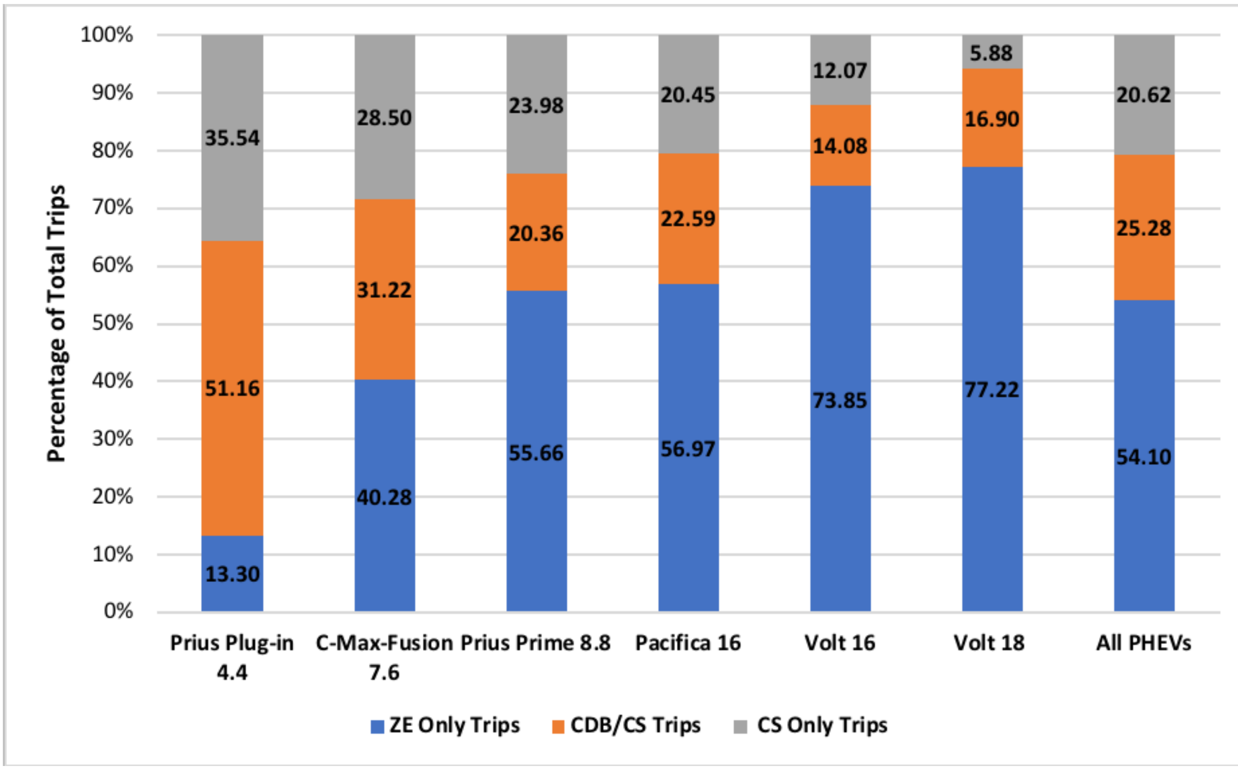


Figure 38. Percentage of Total PHEV Trips by PHEV Driving Mode

Referring to **Figure 38**, we can see that, compared to the other PHEVs, the Volt-18 by far had the lowest percentage of CS only trips and the highest percentage of ZE only trips. In contrast, the Prius Plug-in-4.4 had the highest percentage of CS only trips and CDB/CS trips. At the PHEV fleet level, there was a relatively even split between ZE only trips and CS only or CDB/CS trips. The Volt-18 had a higher share of ZE only trips and lower share of CS only trips than did the Volt-16.

Referring to **Figure 10**, which showed the total share of VMT by trip speed bins and PHEV type, we see that the Volt-18 had a slightly higher share of VMT accomplished at low trip speeds (30 mph or less) and at high speeds (75 mph or more). The incremental battery capacity of Volt-18 compared to Volt-16 is enabling the Volt-18 to do a higher share of blended trips. The share of CDB and CS trips for the Prius Plug-in-4.4 is higher than for other PHEVs, simply due to its smaller battery.

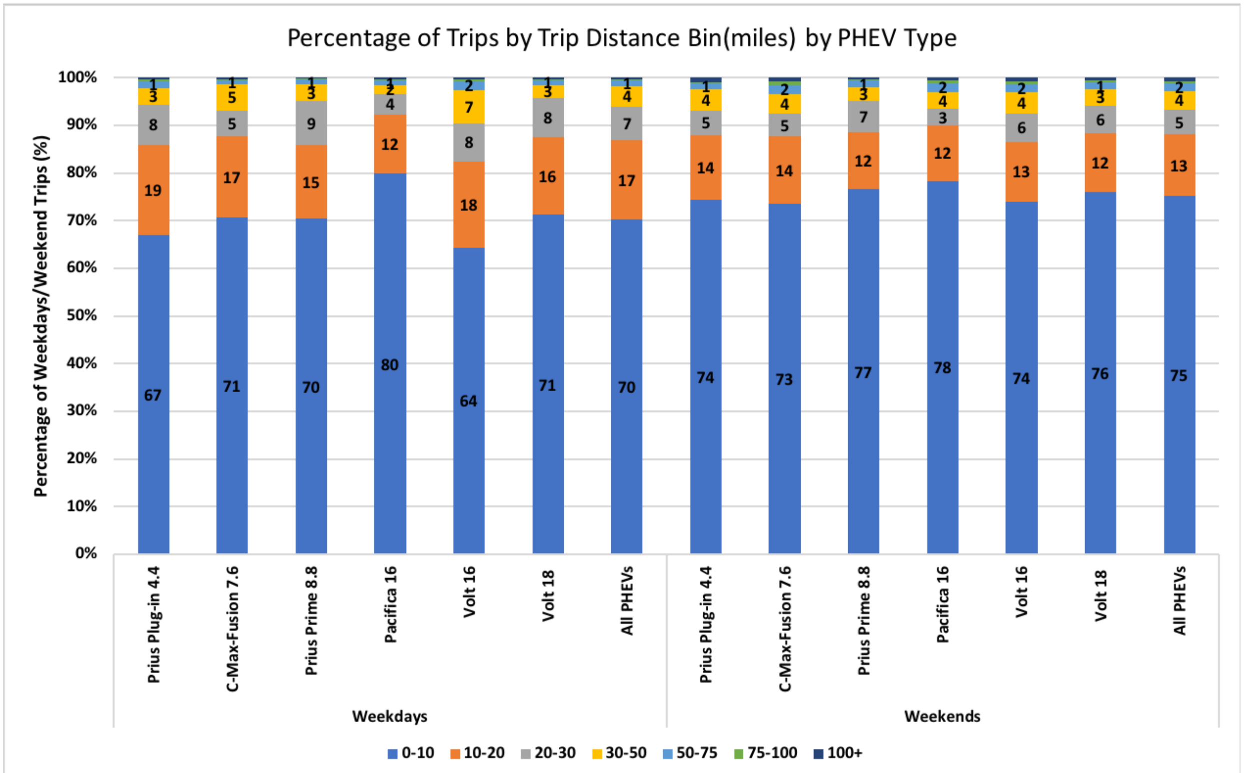


Figure 39. Share of Trips by Trip Distance Bins: Weekdays vs Weekends

Figure 39 shows the percent share of trip distance by trip distance bin on weekdays and weekends. At least 90% of the trips were less than 30 miles for all the PHEV types on weekdays and weekends. During weekends as compared to weekdays, PHEVs, except for the Pacifica-16, are driven on a higher share of trips less than 10 miles and a lower share of trips of 10–20 miles. The Pacifica-16 has a slightly lower share of trips less than 10 miles and around the same share of trips of 10-20 miles, during the weekends as compared to weekdays. The Volt-18 has the same share of trips between 30–50 miles on weekends (3%) as it does on the weekdays (3%); this contrasts with the Volt-16, which has a lower share of 30–50 mile trips on weekends(4%) than it does on weekends (7%).

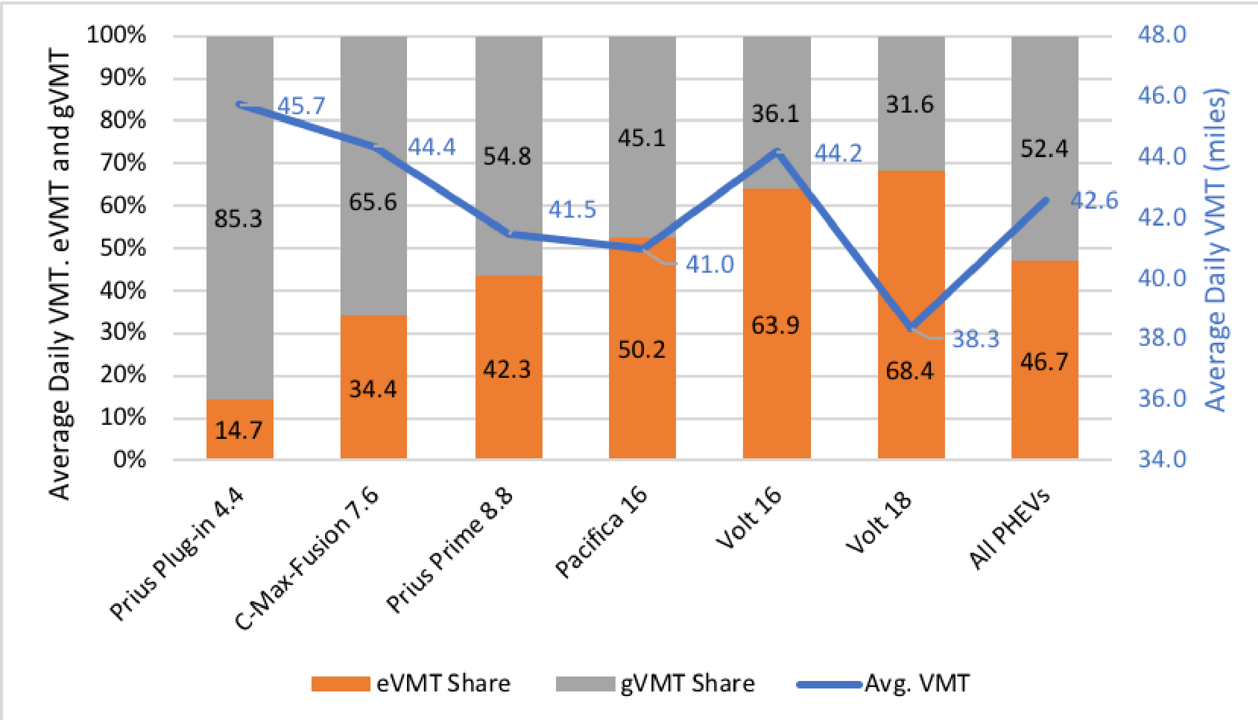


Figure 40. Daily Average VMT, eVMT, and gVMT Share by PHEV Type

Figure 40 shows the average daily VMT, eVMT and gVMT along with the percentage share of eVMT and gVMT. The Prius Plug-in-4.4 had the highest daily average VMT, and the Volt-18 had the lowest daily average VMT. Compared to the Volt-18, the Volt-16 had a higher daily average VMT, higher share of gVMT, and lower share of eVMT. The average daily VMT of the C-max/Fusion-7.6 and the Volt-16 were approximately equal but their split between eVMT and gVMT were opposite, with the Volt-16 eVMT share being 64% and the C-max/Fusion-7.6's gVMT share being 66%.

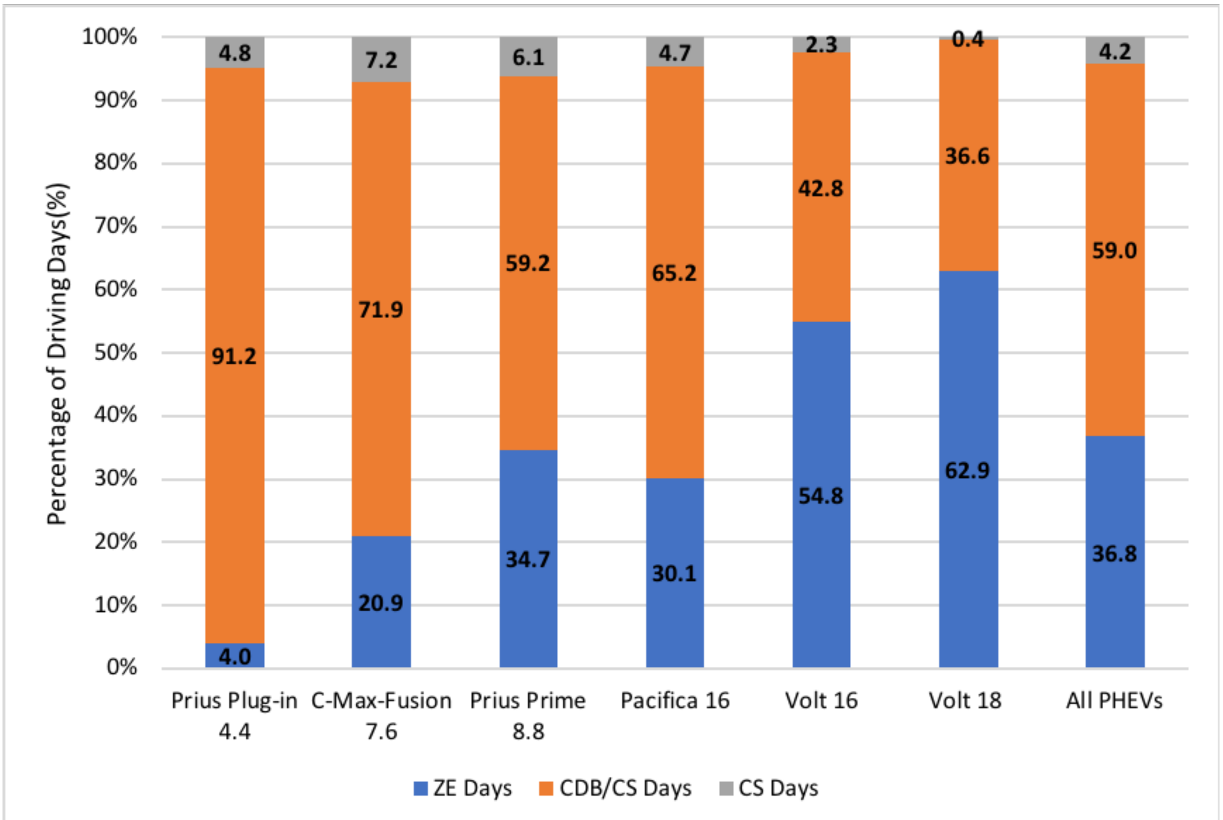
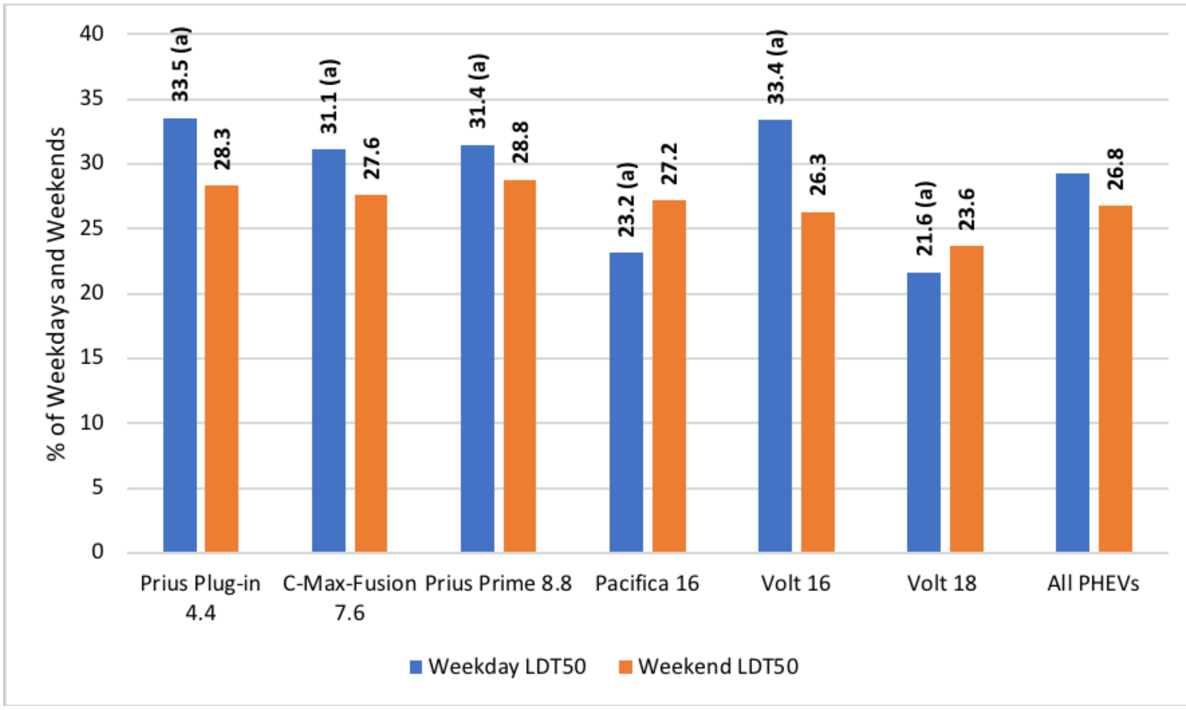


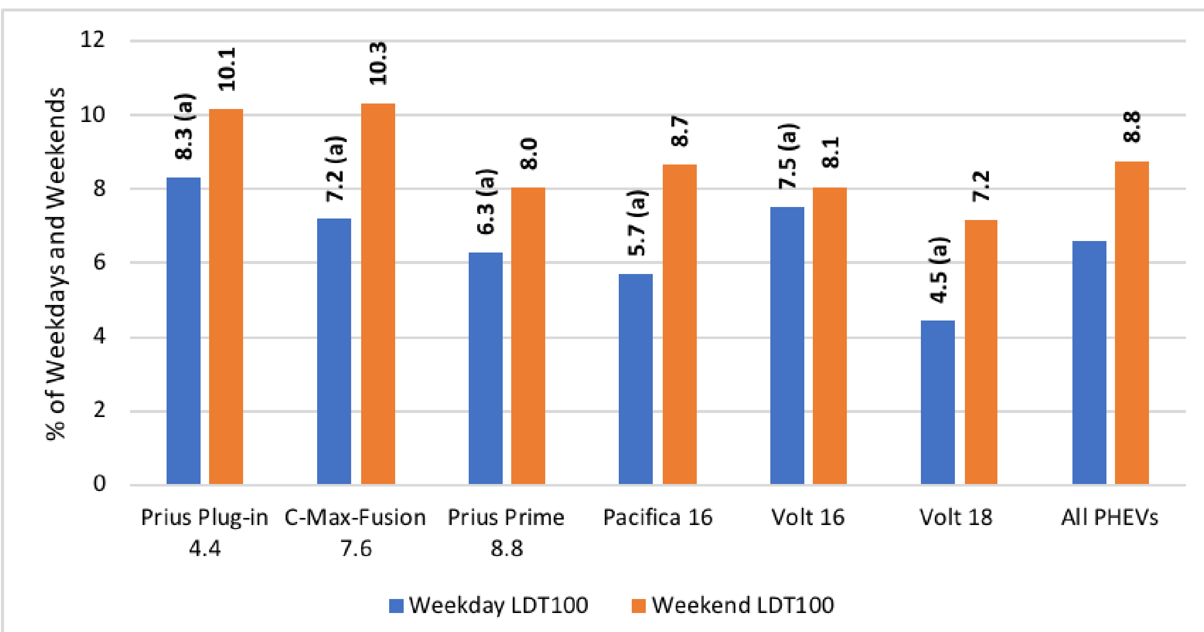
Figure 41. Share of ZE Days, CS Days and CDB/CS Days

Figure 41 shows the share of days the travel was accomplished on electricity alone (ZE only days), gasoline alone (CS only days), and gasoline and electricity (CDB/CS days). It also shows that even among households that charged the vehicle regularly, for all PHEVs, 4.2% of days start with zero SOC, and this is more common for the C-max/Fusion-7.6 than other vehicle types. The Volt-18 had an almost negligible percentage of days when it was driven on gasoline only, with two-thirds of its driving days being ZE only days. Even though the C-max/Fusion-7.6 has a bigger battery than the Prius Plug-in-4.4 has, it had a higher percentage of CS only days.



*If two vehicle models' weekday LDT shares do not share a letter, they are significantly different.

Figure 42. Share of Long-Distance Travel (LDT; 50 miles or more) Days: Weekdays vs Weekends



*If two vehicle models' weekday LDT shares do not share a letter, they are significantly different.

Figure 43. Share of Long-Distance Travel (LDT; 100 miles or more) Days: Weekdays vs Weekends

Figure 42 and **Figure 43** show the share of days on weekdays and weekends, out of the total logged days, that the PHEV was driven 50 miles or more and 100 miles or more, respectively. Pacifica-16 and

Volt-18 had a higher percent of weekends than weekdays when the vehicle was driven 50 miles or more. All the PHEVs had a higher percent of weekends than weekdays when they were driven 100 miles or more.

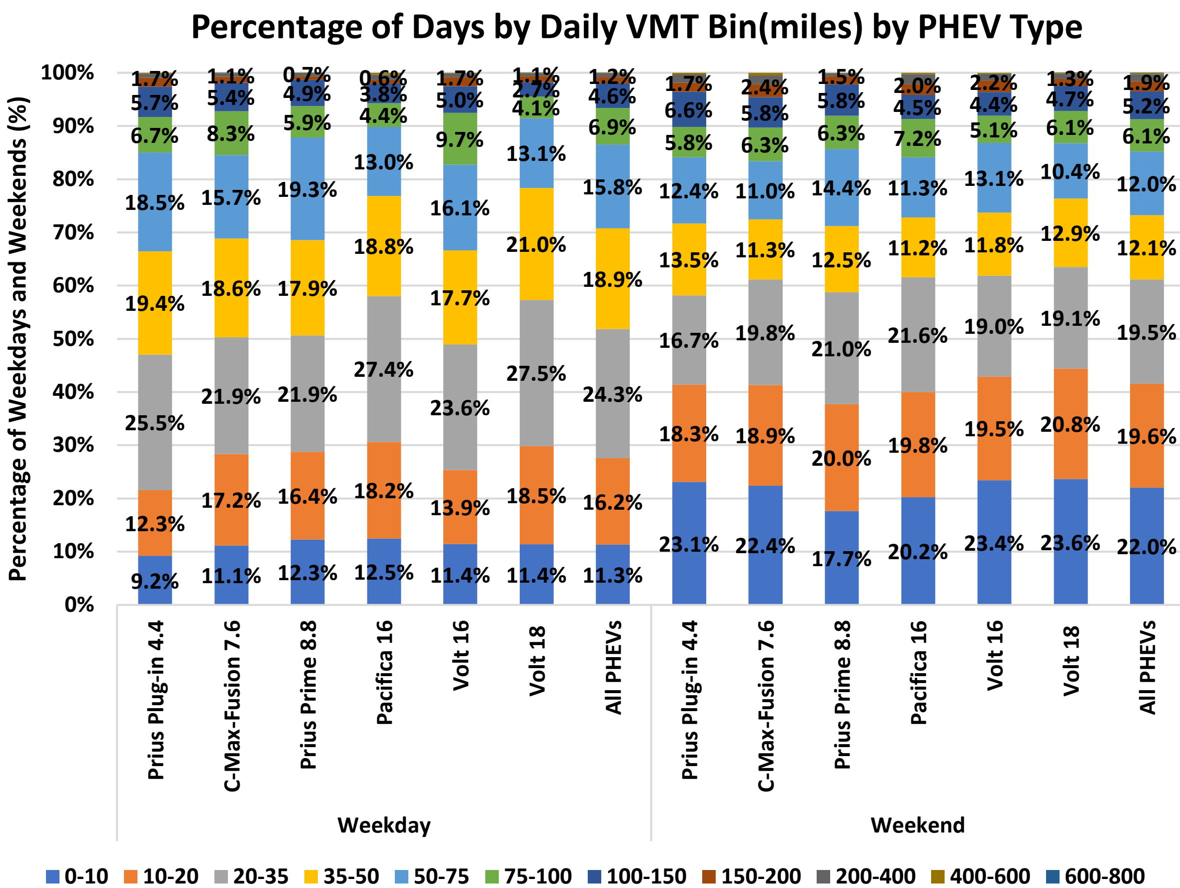


Figure 44. Share of Daily VMT by Distance Bin: Weekdays vs Weekends

Figure 44 shows the percentage of weekdays and weekends by daily VMT bin. Approximately 70% of all the PHEV distances (except for the Pacifica-16 and Volt-18) on weekdays were less than 50 miles. About 84% of the Volt-18 VMT on weekdays were less than 50 miles. During the weekends, for all the PHEVs, 60% of the distances were less than 35 miles. The Volt-18 had the highest percentage of weekdays when it was driven 35–50 miles or 20–35 miles. The percentage of days when VMT was less than 10 miles was almost double on weekends compared to weekdays, for all PHEV types. The percentage of days when the VMT was 75–100 miles was lower on weekends than on weekdays for all PHEVs.

3.6 Plug-in Hybrid Electric Vehicle Charging

Results presented in **Table 14** and depicted in **Figure 45** – **Figure 50** are based on the logger data. **Table 14** summarizes the average number of PHEV charging sessions, kWh charged, and the duration of charging per day by charging level.

Table 14. PHEV Charging Summary Statistics

On Days when the PHEV Charged	PHEV Type	Average Sessions/Day	Average L1 Sessions/Day	Average L2 Sessions/ Day	Average kWh/Day	Average Duration /Day (minutes)	Average eVMT/Day (miles)
	Prius Plug-in 4.4	1.49	1.37	0.12	3.43	150.64	8.19
	C-Max-Fusion 7.6	1.67	0.92	0.75	5.92	252.26	18.13
	Prius Prime 8.8	1.39	0.98	0.41	4.83	228.47	21.12
	Pacifica 16	1.57	0.59	0.98	11.72	344.68	22.77
	Volt 16	1.43	0.66	0.77	9.03	375.84	30.16
	Volt 18	1.29	0.53	0.76	9.80	388.75	30.27
Within the Logging Window Including Days When PHEV Did not Charge	**PHEV Type**	**Average Sessions/Day**	**Average L1 Sessions/Day**	**Average L2 Sessions/ Day**	**Average kWh/Day**	**Average Duration /Day (minutes)**	**Average eVMT/Day (miles)**
	Prius Plug-in 4.4	0.93	0.86	0.07	2.15	94.45	5.59
	C-Max-Fusion 7.6	1.08	0.59	0.48	3.83	163.08	12.48
	Prius Prime 8.8	0.93	0.65	0.27	3.21	151.84	15.35
	Pacifica 16	1.11	0.42	0.69	8.27	243.26	17.35
	Volt 16	1.01	0.46	0.54	6.36	264.50	23.00
	Volt 18	0.76	0.31	0.45	5.76	228.52	21.63

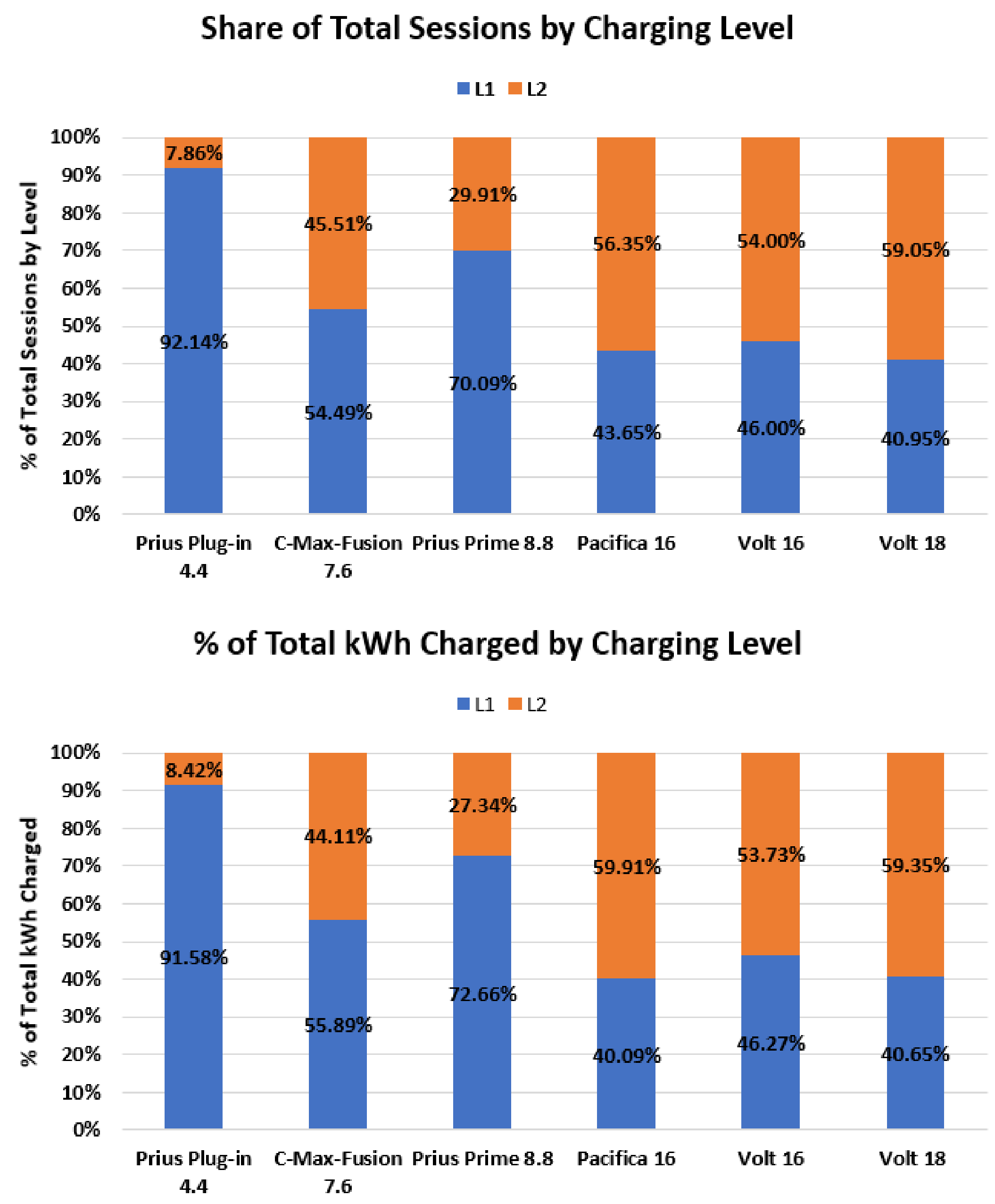


Figure 45. Share of Charging Sessions Charged Energy by Charging Level

Referring to **Figure 45**, L1 charging accounted for most of the Prius Plug-in-4.4, C-max/Fusion-7.6, and Prius Prime-8.8 charging sessions and charging energy. The Volt-16 almost had an even split between L1 and L2 charging sessions and charged energy. For the Volt-18 and Pacifica-16 roughly 40% of its charging sessions and 40% of its charged energy were using L1 charging.

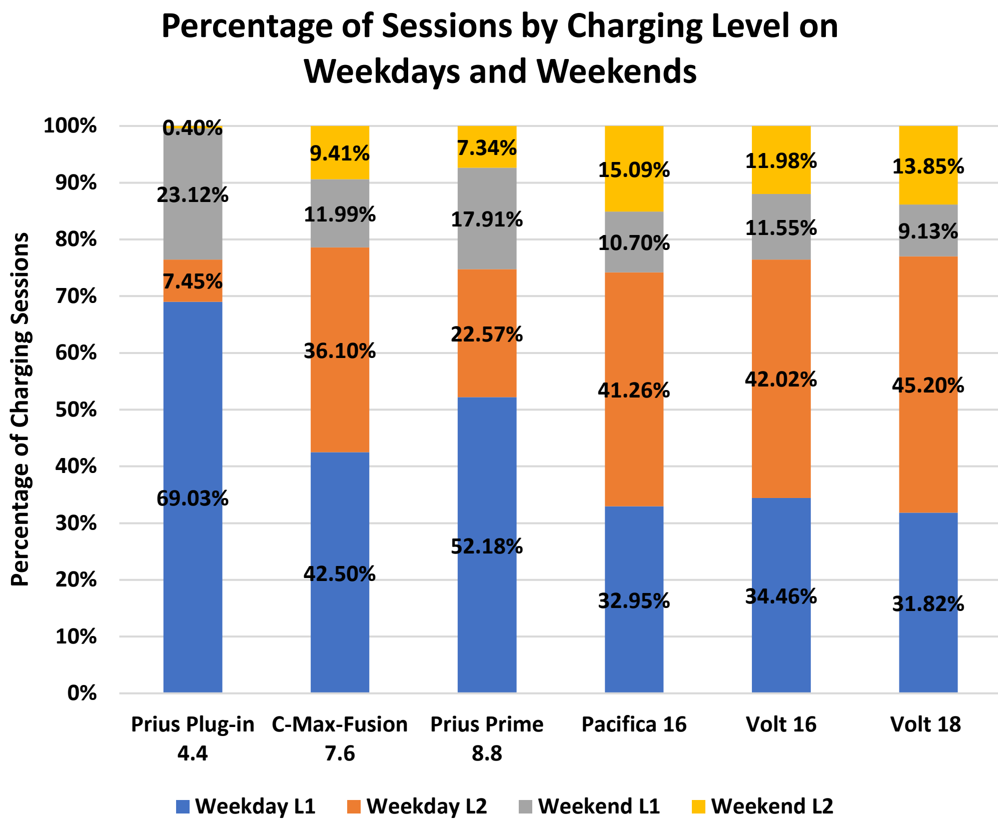


Figure 46. Share of Total Number of Sessions by Charging Level

Referring to **Figure 46**, C-max/Fusion-7.6, Pacifica-16, and Volt-16 had a comparable number of L1 and L2 charging sessions on weekdays. Compared to the Volt-16, the Volt-18 had a slightly lower percentage of L1 charging sessions on weekends and weekdays and a relatively higher percentage of L2 charging sessions on weekends and weekdays.

Figure 47-Figure 48 show the average kWh charged per charging session and the average charging session duration by charging level on weekdays and weekends. Except for the Pacifica-16, on average, all PHEVs were plugged in for relatively longer times (irrespective of the charger level) on weekdays than on weekends and subsequently the average charging energy per session was also higher on weekdays than on weekends. Compared to other PHEVs, the Volt-18 and Pacifica-16 had relatively longer charging sessions and higher charged energy per session (irrespective of the charger level) on weekdays and weekends.

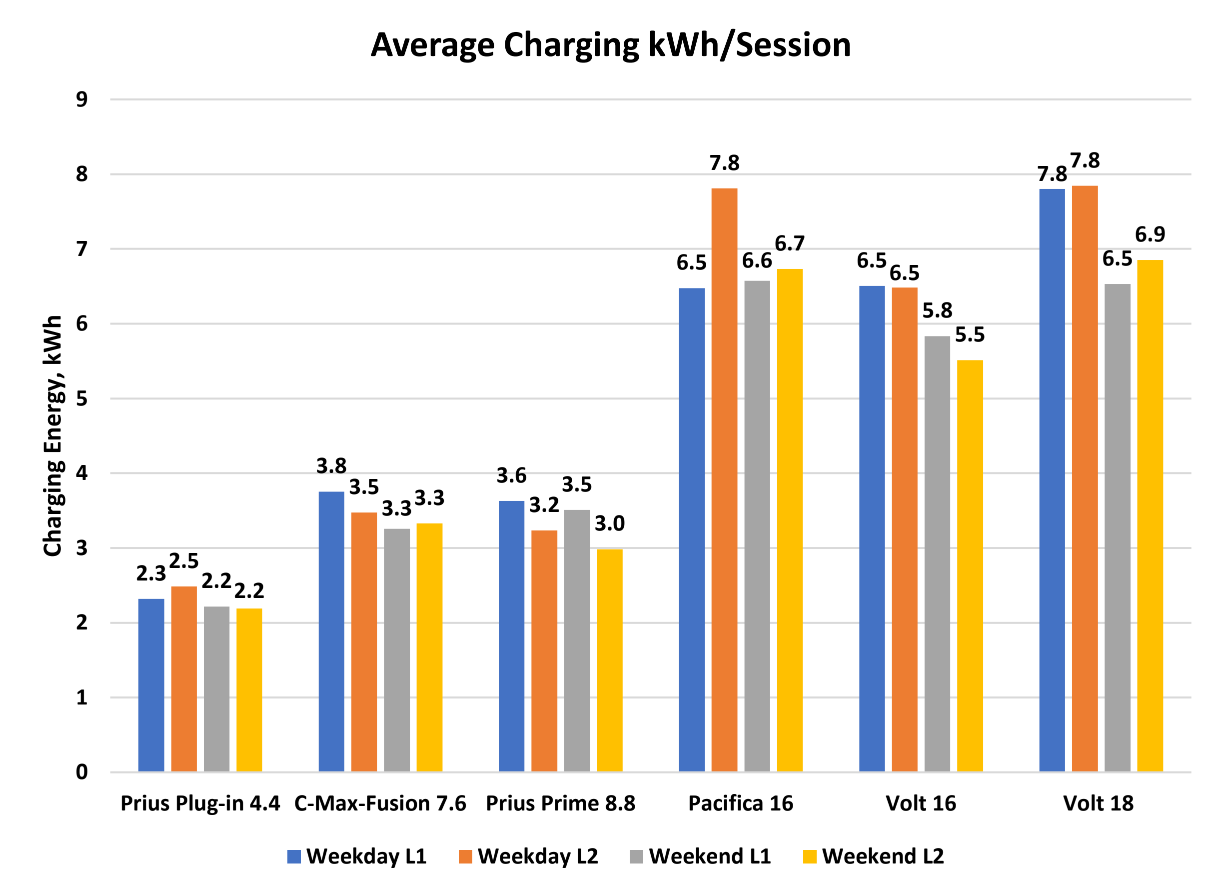


Figure 47. Average L1 and L2 Charging kWh/Session: Weekdays vs Weekends

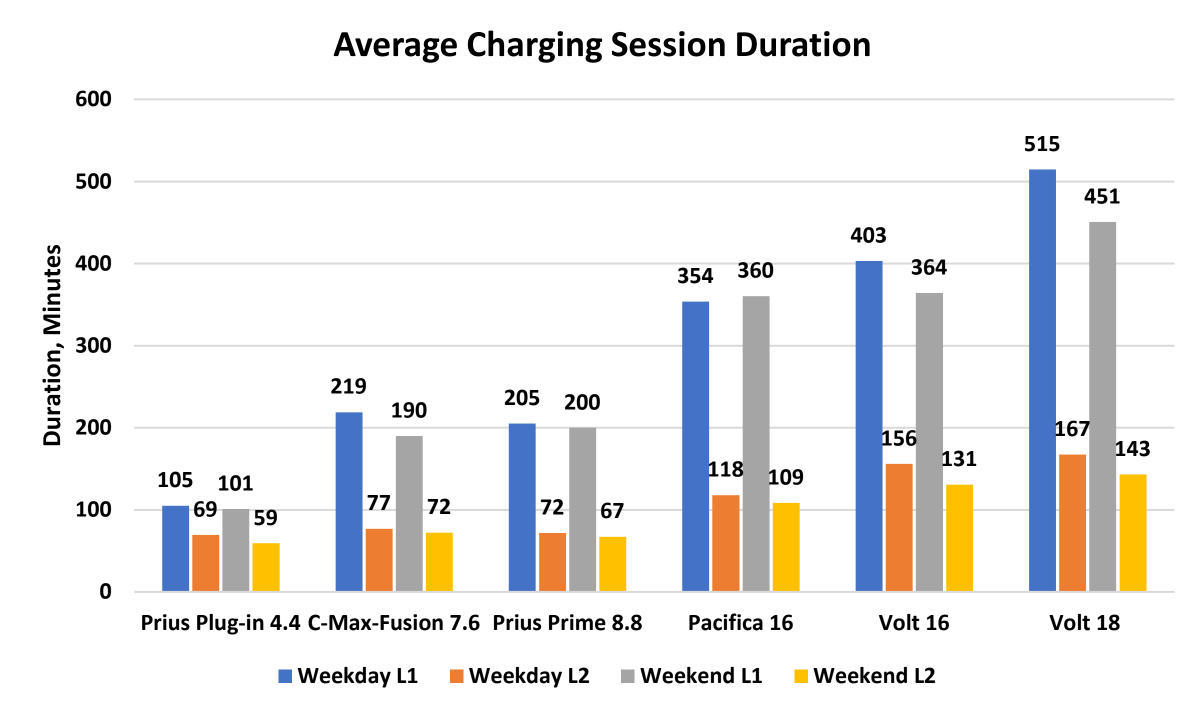


Figure 48. Average L1 and L2 Charging Session Duration : Weekdays vs Weekends

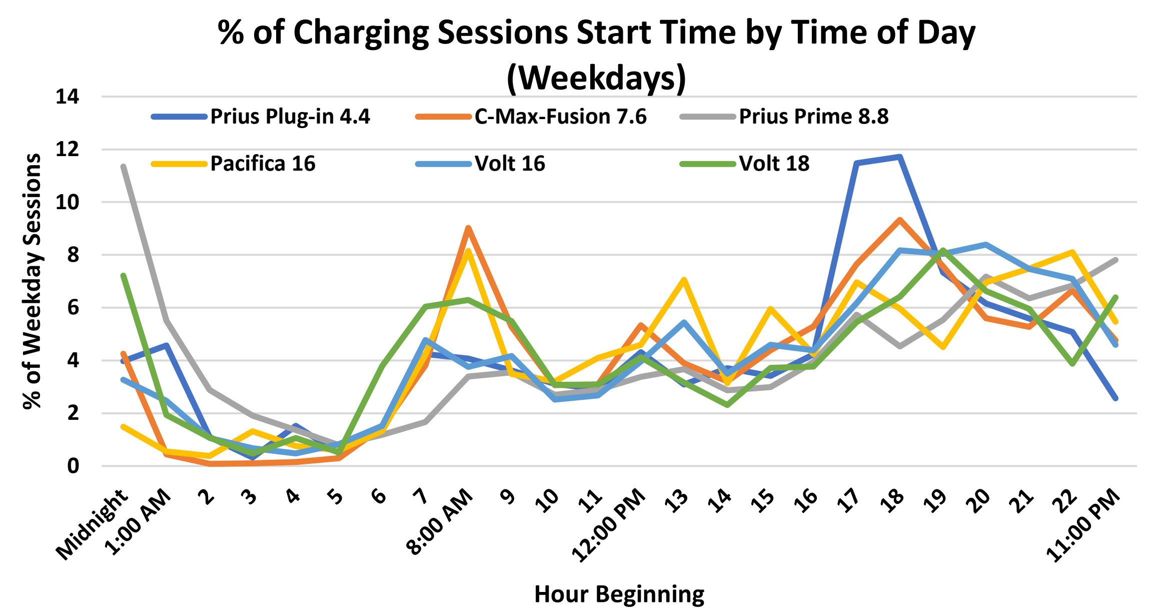


Figure 49. Percentage of Charging Sessions Starting Time (L1 and L2): Weekdays

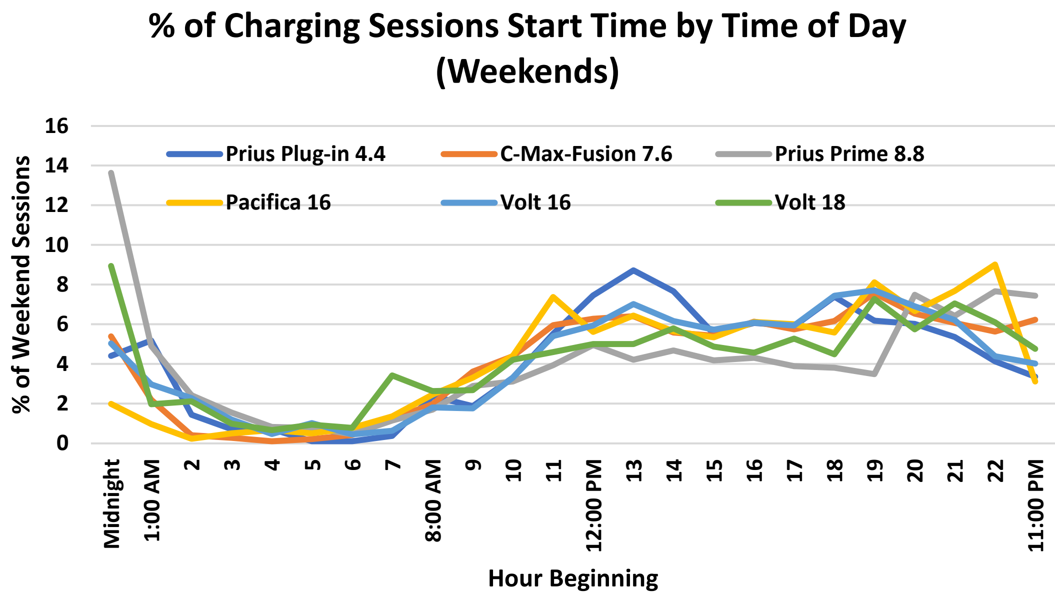


Figure 50. Percentage of Charging Sessions Starting Time (L1 and L2): Weekends

Figure 49 and **Figure 50** show the percentage of charging sessions for each starting time on weekdays and weekends. The percentage of charging sessions noticably spike on weekdays at around 8 am, around noon-1pm, and between 5-7pm; and on weekends at around 1pm, 6pm-8pm and after 11 pm.

3.7 Charging Distance Based on GPS Location of PEVs

We used the survey data to analyze charging location based on self-reported information about home, work, or public charging events. We used the logger GPS location to estimate charging location based on a "crow's flight" distance from the most common vehicle location at 3am while collecting data (designated as "home" in this section), and from the over-night location before the charging. The total number of charging events used in this section is 133,027; of those, 27,031 are out of home events logged from 324 vehicles. Overall, 88% of the recorded level 1 charging events happened at the highest frequency over-night location, meaning that other level 1 charging events may have happened in the household's other "home", or in public locations. Similarly, 72% of the level 2 charging events occured at the same location, and even 4% of the DC fast charging events happened within a one mile distance from home.

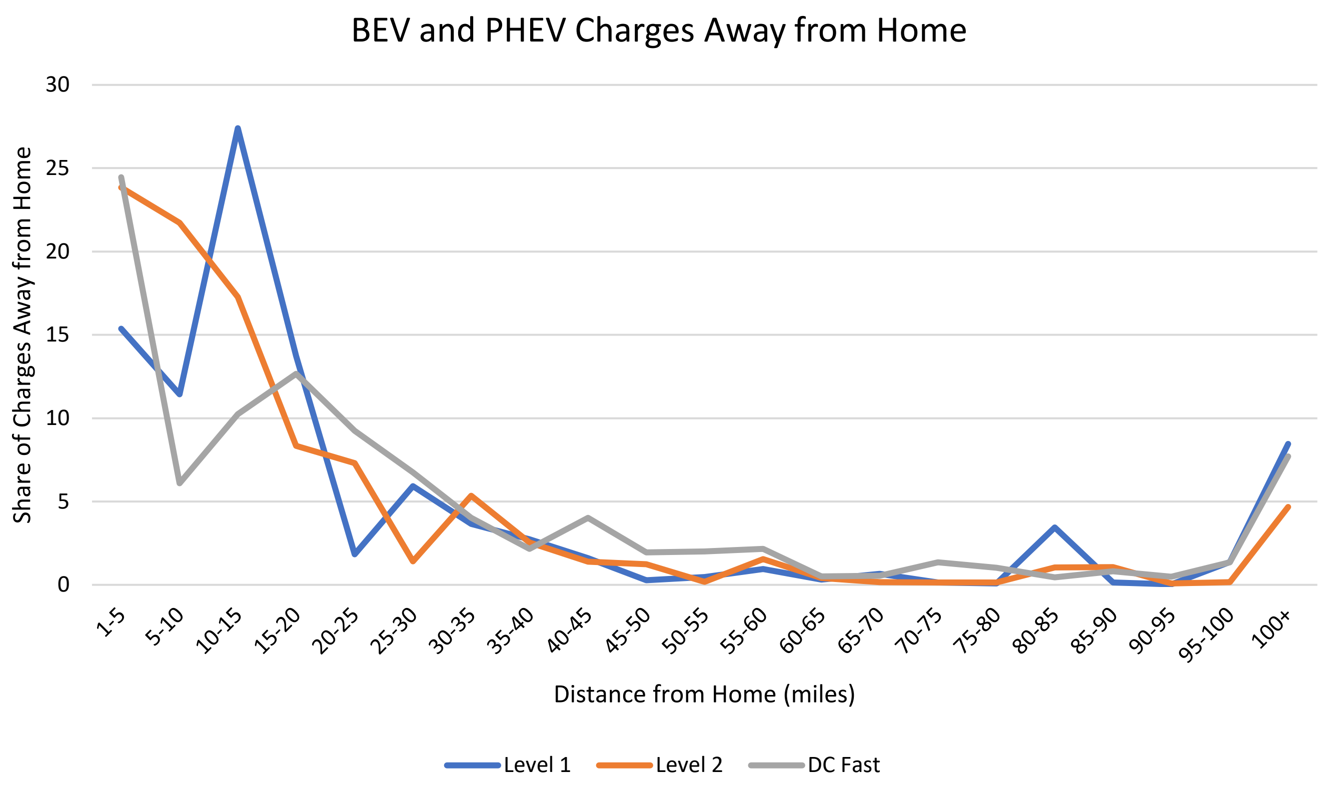


Figure 51. Percentage of Charging Sessions More Than 1 Mile From Home (includes 13% of the L1 events, 29% of L2 events and 97% of DCFC events)

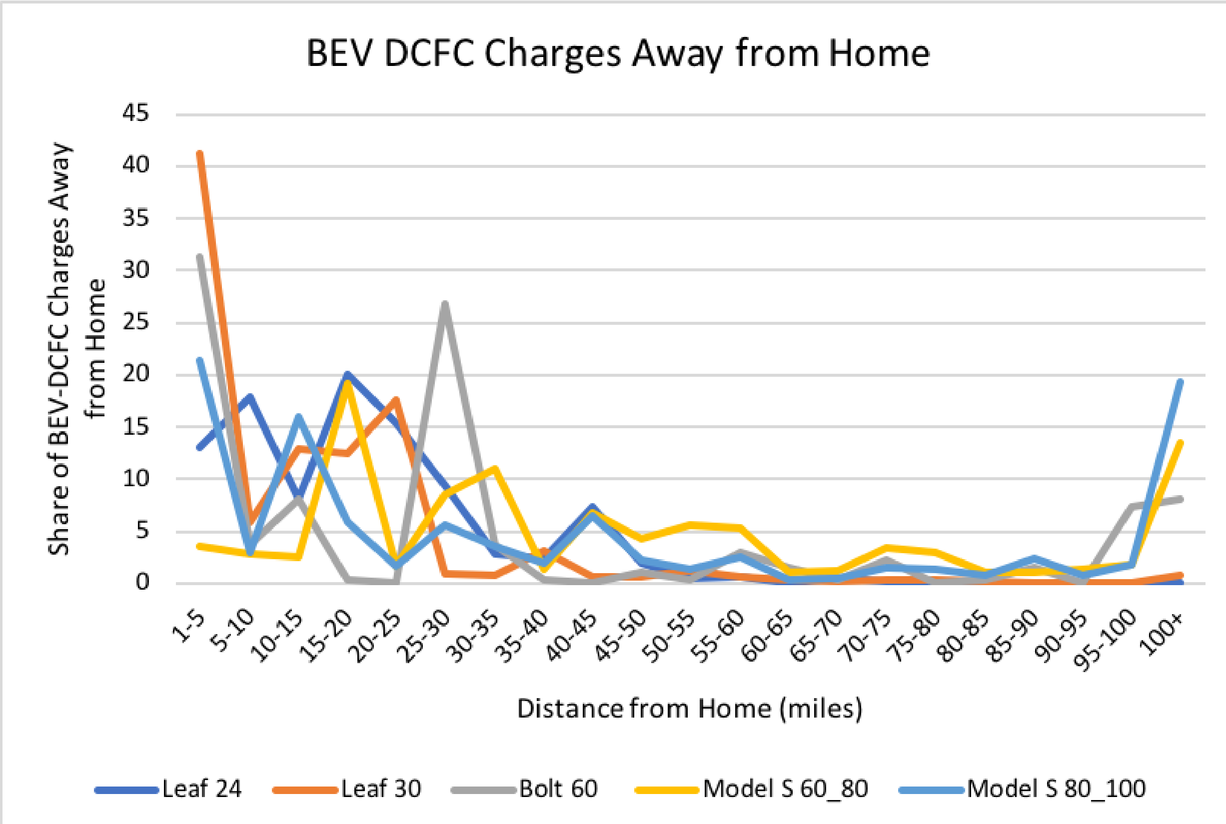


Figure 52. Percentage of DCFC Charging Sessions by BEV Type and Distance from Home

As presented in **Figure 51**, around 25% of the level 2 and DCFC events are within 5 miles from home, while level 1 peaked at 27% within 10-15 miles from home, most likely at the commute location. 63% of the DCFC events are within 25 miles from home and only 8% are more than 100 miles from the main home. Charges that are within 25 miles or more categorize 78% of level 2 events and 70% of level 1 events, respectively. 8% of level 1 events and 5% of level 2 events are more than 100 miles from home. **Figure 52** shows that more than 70% of the DCFC charging events happen within 35 miles from home for the Leaf-24, Leaf-30, and Bolt-60 vehicles. Charging events within 35 miles from home categorize around 50% of the Model S-60_80 and 80_100 vehicles, respectively. When exploring the number of DCFC charging events based on one way trips (using two thirds of the BEV travel range to reflect the difference between straight lines and the road network) we conclude that 99% of the Leaf-24, 98% of the Leaf-30, 80% of the Bolt-60 and more than 71% of the Tesla charging events are within range for a round trip from home, if starting the day with a full battery.

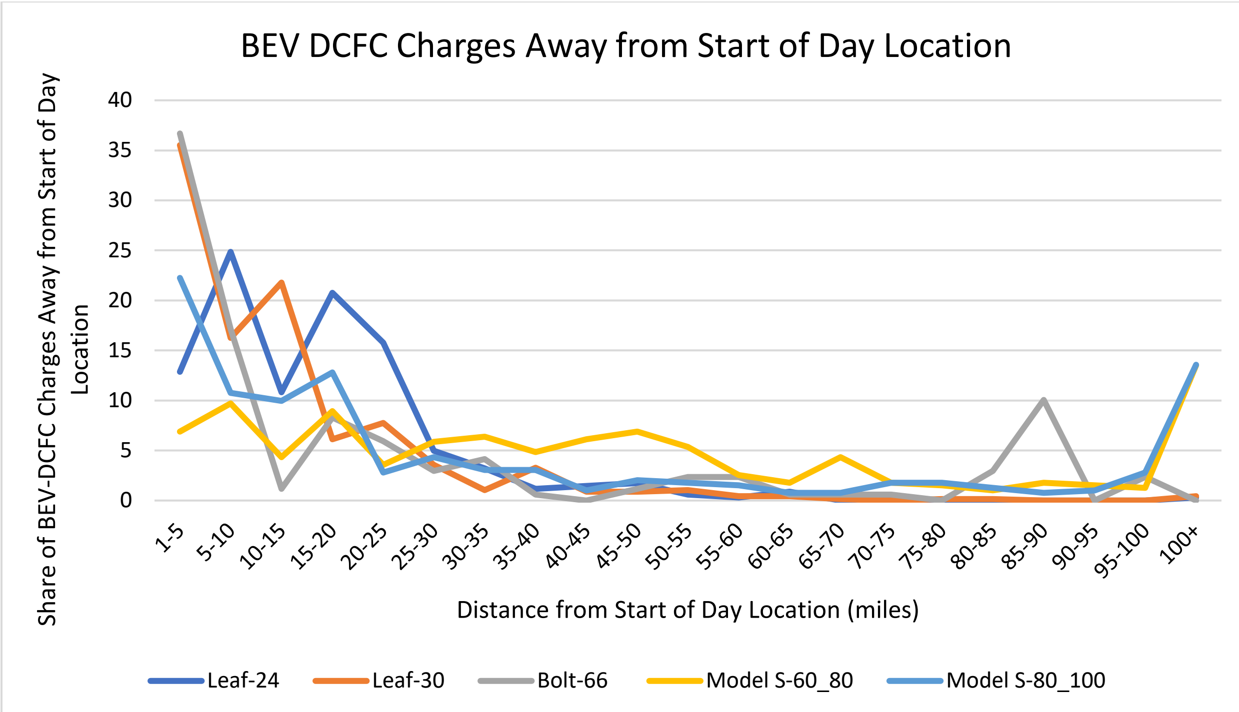


Figure 53. Percentage of DCFC Charging Sessions by BEV Type and Distance from Last Night Location

Using the "last night's" location rather than the "home" location reduces the distance even more, especially for the longest trips. Away from the start of day location, around 85% of DCFC charges were within 25 miles from the start of day location for the Leaf-24 and Leaf-30, whereas the Bolt-60, Tesla 60_80 and 80_100 had a share of 69%, 33%, and 59% respectively. The Tesla 80-100 DCFC charging sessions over 100 miles from home drops from 19% to 14%, most likely because of multi-day trips that end and start on the road without an overnight charging opportunity. This method also accounts for long vacations, summer homes, etc. that result in short trips every day but many charging events far from home.

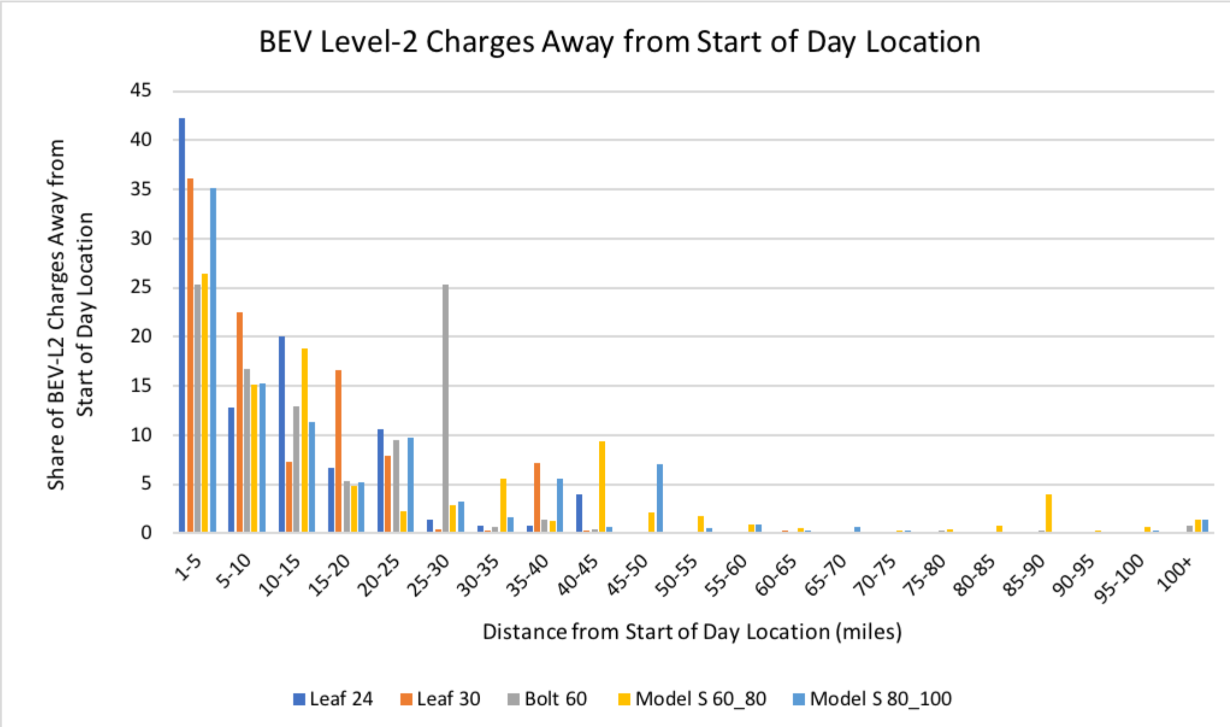


Figure 54. Percentage of Level 2 Charging Sessions by BEV Type and Distance from Last Night Location

As expected, most of the L2 events are within 1-25 miles from home, with additional smaller spikes for Tesla 60_100 and 80_100 who travel longer trip distances. There is also a noticeable 25% share of L2 events within 25-30 miles for Bolt-60 BEVs. Overall, level 2 is being used at the destination, and therefore most events are at work and within the vehicle range.

4 Household Level Analysis of PEVs

Self-reported trip diaries of travel behavior surveys (PSRC TCS 2006, Kunzmann and Masterman 2013, TxDOT 2015, FHWA 2017) are often used as the starting point for generating the set of assumptions about PEV driving and charging behavior. Instrumented ICE data has better spatio-temporal resolution compared to trip diaries(Aviquzzaman 2014). This still cannot characterize PEV travel patterns because of the implicit assumption that ICEs and PEVs are operated the same manner. It dilutes the risk perception associated with modern technology adoption, especially in the case of range anxiety associated with ZEVs. stated and revealed preferences of current PEV owners are increasingly being used to obtain information about how current PEV owners drive and charge(Nicholas, Tal et al. 2017). Instrumented PEVs by far are the best source of data compared to cross sectional or longitudinal survey data of ICEs and stated or revealed preferences of existing PEV users(Nicholas, Tal et al. 2017, Raghavan and Tal 2019). Prior research advocates the need to have realistic representation of PEV usage to increase their usefulness to policymakers. Assuming homogenous usage of a specific PEV model across diverse strata of demographics and travel needs, and subsequently their emission reduction potential presents an inaccurate picture of the day-to-day substitution patterns between an ICE and PEV. Even if high-resolution data from actual PEV usage is available, it is necessary to observe them over a longer duration of time to capture rare and infrequent long-distance travel, which may have a bearing on the purchase or lease and use of the vehicle.

A crucial aspect, which is often overlooked in majority of PEV usage studies in literature as well as in the policy realm, is the household (HH) context. While evaluating travel behavior and emissions implications of PEV adoption, household context is pivotal because day-to-day activities are allocated between PEVs and the other vehicles in the household on a per-trip basis at disaggregated temporal levels. Furthermore, in a survey of 15,000 PEV owners in California, roughly 45% of BEVs and 42% of PHEVs belong to two-car households(Turrentine and Tal 2015, Nicholas, Tal et al. 2017). PEVs have unique features that will alter how they are driven and charged compared to ICEs. Depending on travel needs, individual driver preferences, fuel, and electricity costs, charging access and opportunities, VMT by the PEV has cascading effects on VMT of other household vehicles. Apart from the quantity of miles, it is also important to account for the derived impact of miles (GHG/mile) PEVs substituted at the household level. Therefore, studying PEV usage in isolation may lead to inaccurate estimates of their net environmental impacts, since it is based on partial information.

To ensure parity when comparing different PEV households, we excluded households that have more than 1 PEV of the same type, irrespective of the number of ICEs in the household (for example a 3-car household with 2-Leaf and one ICE or a 2-car household with 2 Volts were dropped). Furthermore, to understand substitution and emission profile at the household, the sample size of the household was limited to single PEV(BEV or PHEV), single ICE-PEV(ICE-BEV or ICE-PHEV), double ICE and single PEV (ICE-ICE-BEV or ICE-ICE-PHEV), and household with both BEV and PHEV (BEV-PHEV or ICE-BEV-PHEV). The above selection criteria was deemed fit because 65% of California households have 2 or less vehicles ; 16% of California households have 3 vehicles(McGuckin and Fucci 2017). Since only 9% of California households have 4 or more vehicles (McGuckin and Fucci 2017), we excluded households and the respective vehicles with 4 or more vehicles from our analysis. In addition, as outlined in Section 3, the BMW i3 REX and its households were excluded because the logger could not acquire any data from them. Out of the 364 Households that were logged, 61 households were dropped which accounted for all the BMW i3, Soul EV, and Audi Etron households as well as any households with over three vehicles or an extremely low share of PEV/ICE driving days.

The sample size of PEVs used in the household level analysis differs from the sample size referred in **Table 3**-**Table 6** simply because of excluding the households and their vehicle holdings due to household car ownership patterns exceeding the 3 and/or the type of vehicles belonging to the household (double BEV or PHEV of the same type). In our household (HH) level analysis, there are 117 BEVs (21 Leaf-24, 25 Leaf-30, 27 Bolt-60, 19 Tesla Model S-60_80, 22 Tesla Model S-80_100, and 3 RAV4 EV-42) and 197 PHEVs (20 Prius Plug-in-4.4, 50 C-max/Fusion-7.6, 26 Prius Prime-8.8, 26 Pacifica-16, 41 Volt-16, and 34 Volt-18). The total household level sample size is 303.

Table 15 summarizes the multi-PEV HHs with and without an ICEV. Approximately 60% of the HHs in our study had two-vehicles, 30% had one vehicle, and 10% had three vehicles. Out of the 85 single-vehicle HHs, 63 had a PHEV and 22 had a BEV. Referencing **Figure 55**-**Figure 56**, Of the 190 two-vehicle HHs, 111 have an ICEV and a PHEV, 72 have an ICEV and a BEV, and 7 had a BEV and PHEV. Among the 28 HHs with three-vehicles, 12 had two ICEVs and a PHEV, 12 had two ICEVs and a BEV, and 4 had an ICE, a BEV, and a PHEV. Overall, 96% (292 out of 303) of the HHs had only one PEV (BEV or PHEV). There were 85 single-vehicle HHs with only a BEV or a PHEV, 183 two-vehicle HHs with an ICEV and a PHEV or BEV, 24 three-vehicle HHs with a PEV and two ICEVs, and 11 multi-PEV HHs (with and without an ICEV). Summary statistics and results presented in **Table 15** – **Table 24** and depicted in **Figure 55** – **Figure 72** are based on the logger data.

Compared to the vehicle level analysis, where we focused on the days when the PEV was driven or charged, in the HH context, it was important to have parity in terms of the number of days each vehicle was logged within each HH as well as across different HHs. When comparing two HHs with the same number of vehicles and vehicle types—for example two-vehicle HHs with one ICEV and one Leaf-24—if the first HH was logged for 350 days and the second household was logged for 400 days, at an aggregate level, comparing the VMT and energy consumption (gasoline and electricity) between these two HHs would be inaccurate and could potentially lead to false conclusions about PEV usage and the HH level eVMT. It was crucial to classify the days on which we had no data (no trips or charging sessions) as unobserved or unused to avoid over- or underestimating HH level eVMT, which depends on the VMT of not just the PEVs but also the ICEVs.

Unobserved days typically denoted days when we knew the data logger had a problem, and the unused days denoted days when we had no issues with the data logger and the vehicle was simply not used. Reasons for the vehicle not being used could be that the study participant was out of town/traveling/taking a vacation, the car was temporarily unavailable because of service/maintenance, or there was no demand for travel on that day. Consider the same example of 2 HHs each having an ICEV and a Leaf-24. If the ICEV in one HH had data logger issues for a few weeks, and we had data from the BEVs during the period, if we incorrectly assume the ICEV was not used, then eVMT will be overestimated.

We used the days the individual vehicles (ICEV, BEV, PHEV) were logged (used and unused days) to annualize all the key metrics (trips, charging sessions, VMT, driving/charging energy, gasoline consumed).

The HH level analysis section is organized as follows: we present first the results from BEV HHs (only a BEV; an ICEV and BEV; and two ICEVs and a BEV) and then the results from PHEV HHs (only a PHEV; an ICEV and PHEV; and two ICEV and a PHEV). Finally, since only 4% of the HHs (11 HHs in total) in our study had both a BEV and PHEV (with or without an ICEV), and 9 of these 11 HHs did not have any of the same types of BEVs and PEVs, their results are presented separately and are not analyzed as a group. **Table 15** shows the breakdown of double PEV HHs.

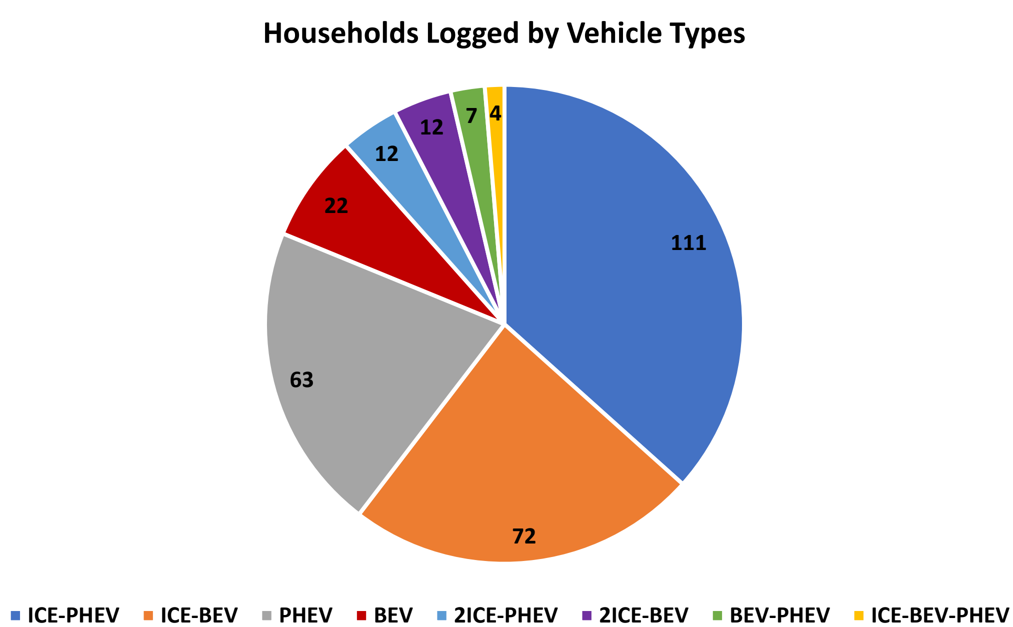
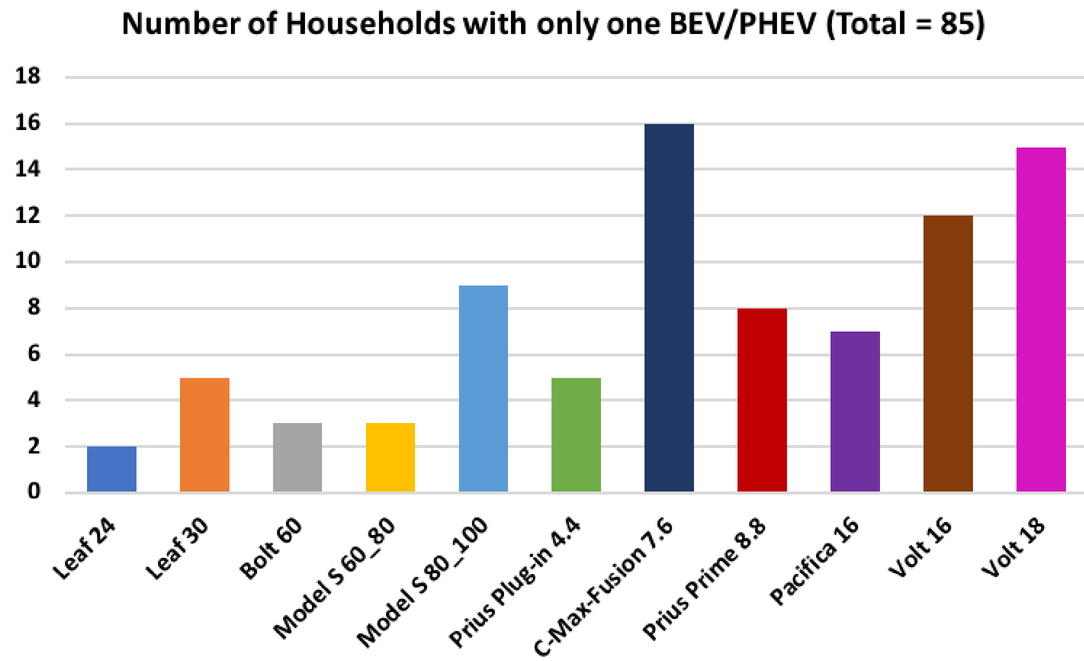


Figure 55. Composition of Households Included in the Analysis



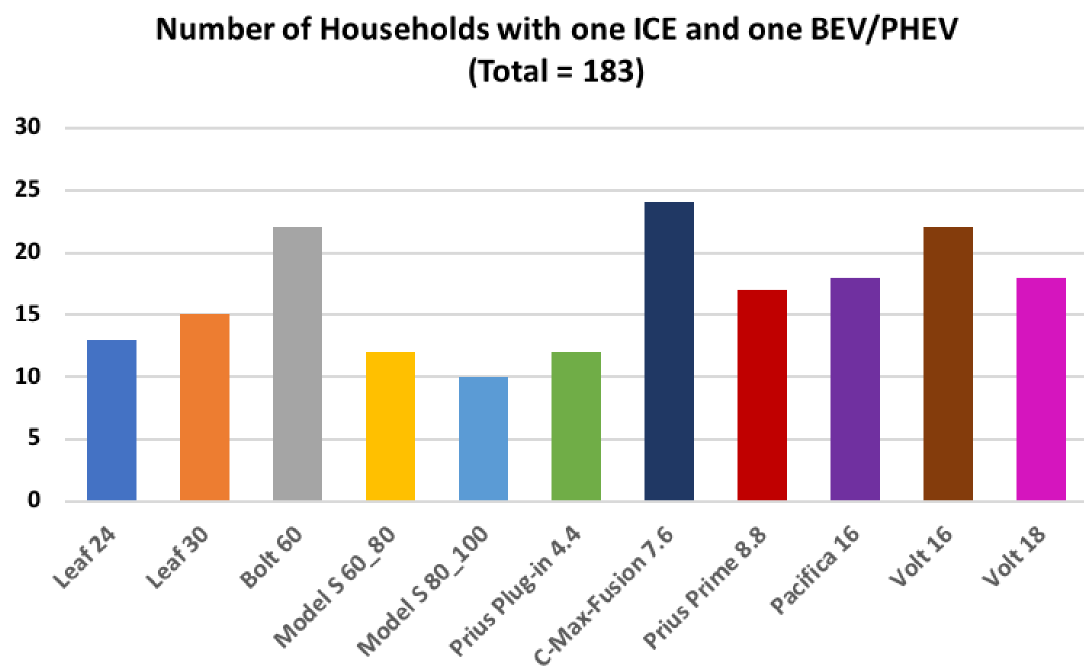


Figure 56. Number of Households with only One BEV or PHEV Logged in the Study (Upper) and Number of Two Car Households with One ICEV and One BEV or PHEV Logged (Lower)

Table 15. Double-PEV (1 BEV and 1 PHEV) With or Without an ICEV (N=11)

Type of HH	BEV, PEV in the HH	Number of HHs
ICE-BEV-PHEV	RAV4 EV-42, C-Max/Fusion-7.6	1

Type of HH	BEV, PEV in the HH	Number of HHs
ICE-BEV-PHEV	Leaf-24, C-Max/Fusion-7.6	2
ICE-BEV-PHEV	RAV4 EV-42, Volt-16	1
BEV-PHEV	Model S-60_80, Volt-16	1
BEV-PHEV	Leaf-30, Volt-18	1
BEV-PHEV	Leaf-24, C-Max/Fusion-7.6	1
BEV-PHEV	Model S-60_80, Pacifica-16	1
BEV-PHEV	Bolt-60, Prius Prime-8.8	1
BEV-PHEV	Leaf-24, Volt-16	1
BEV-PHEV	RAV4 EV-42, Prius Plug-in-4.4	1

4.1 Households with a BEV Only or BEV and ICEV

Table 16 summarizes the (average) annualized estimates of key metrics such as eVMT, gVMT, HH VMT, UF, and energy consumption (driving and charging). **Figure 57** depicts the HH UF in BEV HHs by number of vehicles in the HH and the type of BEV in the HH.

Table 16. (Average) Annualized Estimates of VMT and Energy Consumption in BEV HHs

HH Type	Num. HHs	BEV	BEV Trips	BEV eVMT	BEV kWh Driving	ICEV gVMT	ICEV Fuel (gallons)	HH VMT	HH UF
2-ICEV-BEV	2	L24	1191	12287	3000	18610	722	30897	0.41
	4	L30	1425	12982	3400	20682	891	33664	0.39
	1	B60	1395	22917	5285	16316	888	39233	0.58
	2	T60	1187	22276	6918	8900	395	31176	0.71
	3	T80	405	10483	3462	22457	1024	32940	0.33
ICEV-BEV	13	L24	1483	10326	2395	10908	451	21233	0.49
	15	L30	1456	12352	3218	8689	335	21040	0.57
	22	B60	1438	13399	3338	9530	387	22929	0.58

HH Type	Num. HHs	BEV	BEV Trips	BEV eVMT	BEV kWh Driving	ICEV gVMT	ICEV Fuel (gallons)	HH VMT	HH UF
	12	T60	984	17716	6000	7885	393	25601	0.65
	10	T80	916	14797	5118	7154	334	21951	0.67
BEV	2	L24	1235	7955	1806	0	0	7955	1
	5	L30	1137	7169	1892	0	0	7169	1
	3	B60	1336	13489	2500	0	0	13489	1
	3	T60	1085	9797	3322	0	0	9797	1
	9	T80	1054	13639	4889	0	0	13639	1

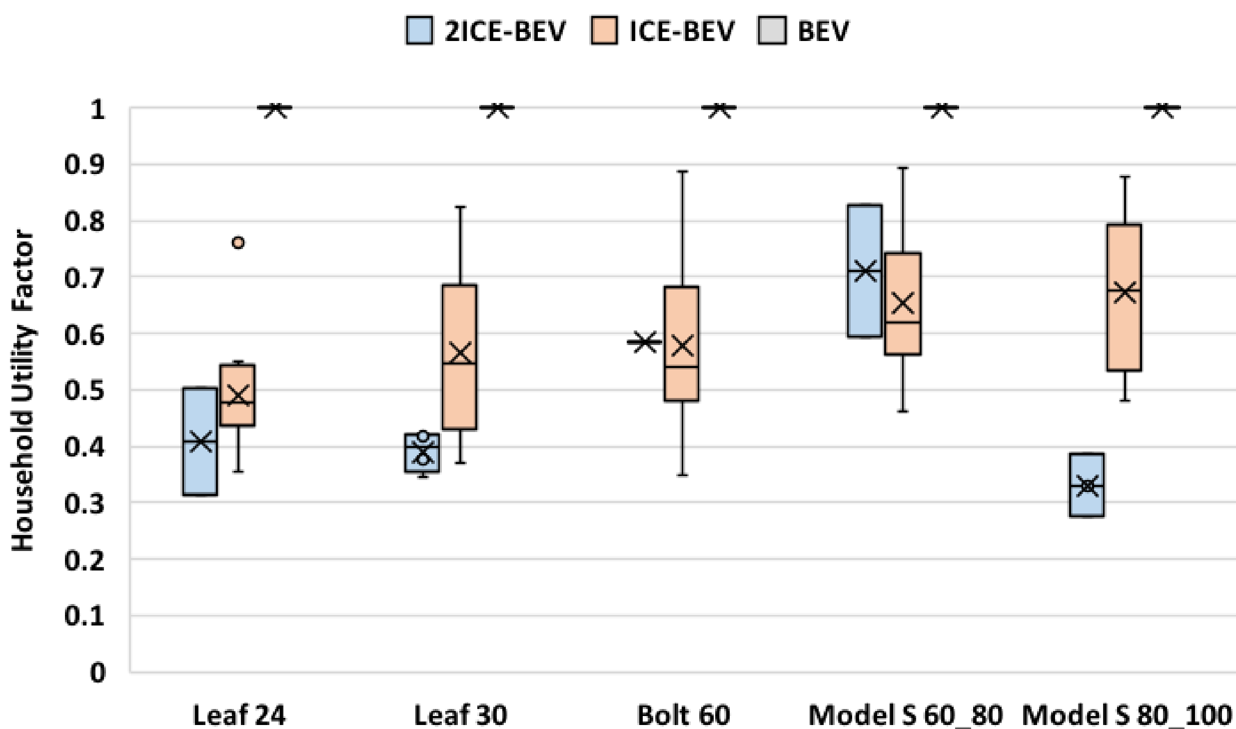


Figure 57. Household Utility Factor by BEV Type and Household Car Composition

Some of the key insights regarding the HH level UF of HHs with ICEVs and BEVs are as follows:

- The average UF of HHs with a Bolt-60 with either one or two ICEVs were relatively similar (0.578 vs. 0.584).

- On average, among two-vehicle HHs and three vehicle HHs, HHs with a Model S-60_80 and two ICEVs had the highest UF, whereas HHs with a Model S-80_100 and two ICEVs, had the lowest UF.
- The UF in ICEV-BEV HHs increased with the battery capacity.
- HHs with a Bolt-60 tended to have a higher average daily HH VMT relative to other BEV types in HHs with either one ICE or two ICEs.

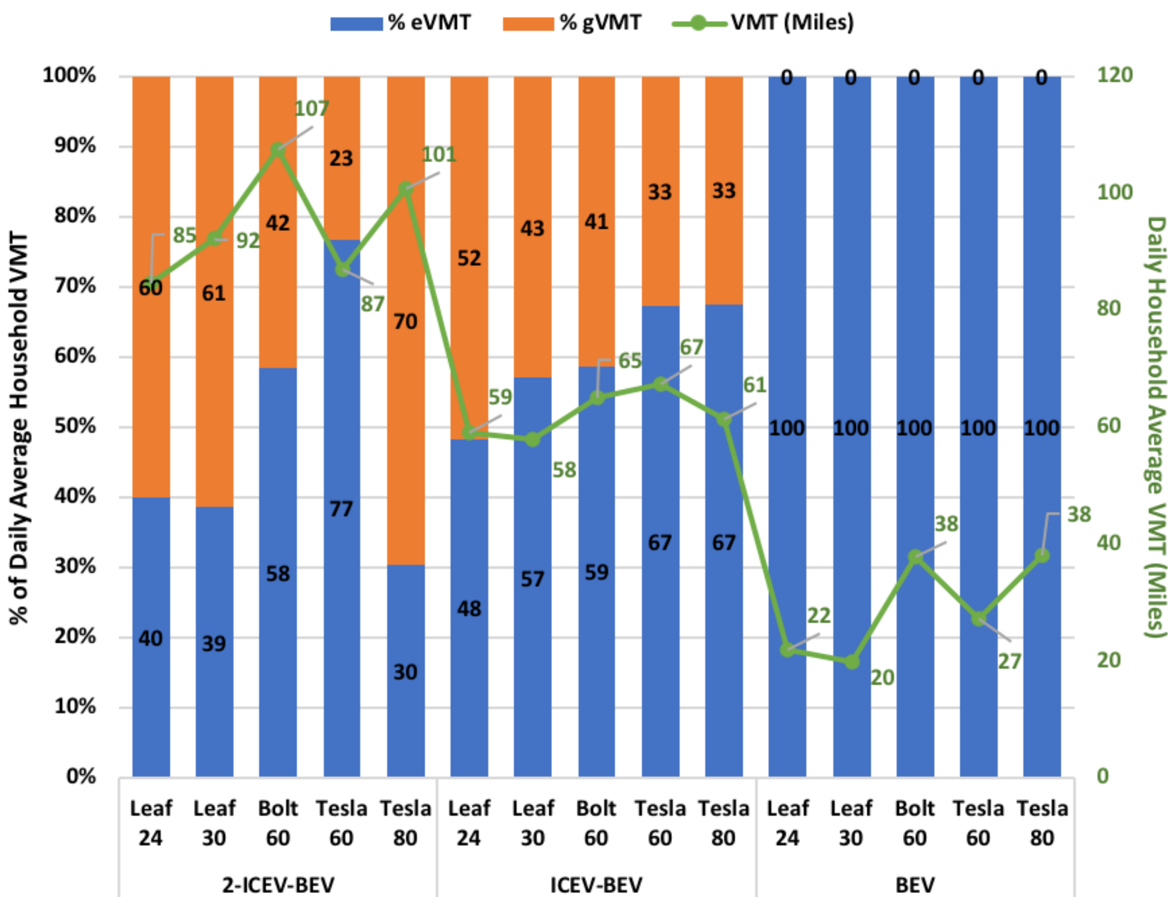


Figure 58. HH Average Daily VMT in HHs with BEVs, Showing the eVMT and gVMT Percentages

Figure 58 shows the average daily HH VMT and the share of eVMT and gVMT in BEV HHs. Three-vehicle HHs with two ICEVs and one BEV, apart from having a Leaf-24, had higher average daily HH VMT than did three-vehicle HHs with one Model S-60_80 BEV. HHs with two ICEVs and one Leaf had nearly two-thirds of their VMT attributable to gasoline-power (gVMT). In two-vehicle HHs, there is a trend of higher eVMT as battery size increses.

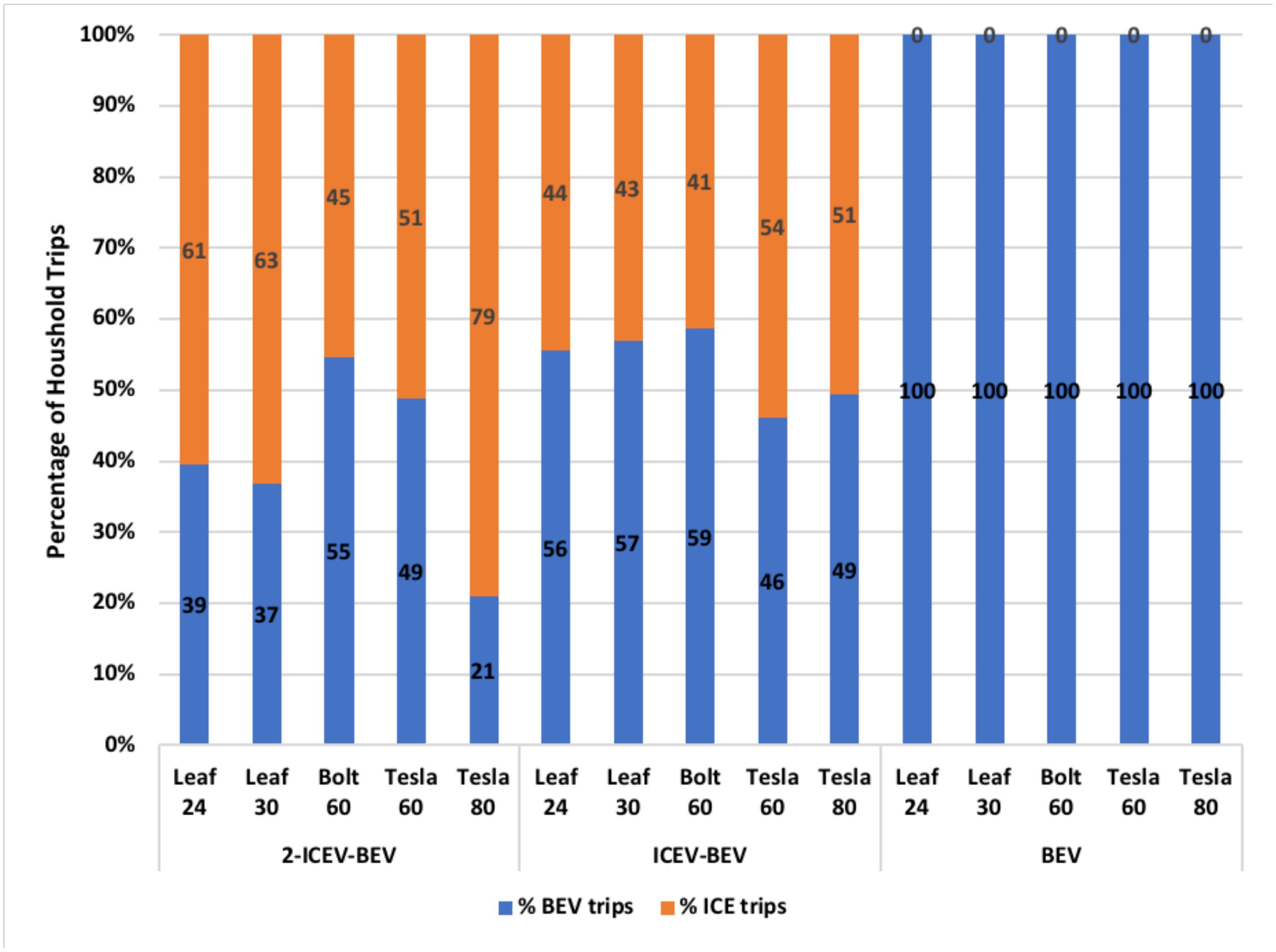


Figure 59. Percentage of BEV and ICEV trips in HHs with BEVs

Figure 59 summarizes the percentage of HH trips taken using the BEV and the ICEVs. In three-vehicle HHs, the household with two ICEVs and one Bolt-60 had the highest percentage of BEV trips (55%) whereas HHs with two ICEVs and one Model S-80_100 had the lowest percentage of BEV trips (21%). On average, the BEV share of HH trips in two-vehicle HHs was approximately 60% for HHs with one ICEV and either one Leaf or Bolt-60 and approximately 50% for HHs with one ICEV and one Tesla. **Figure 58** and **Table 16** together show that, in two-vehicle BEV HHs, roughly 50% of HH trips were taken using the ICEV, but the share of miles replaced by the BEV is noticably different between HHs with a smaller battery capacity BEV and a larger battery capacity BEV. The percentage of total HH VMT driven using the ICEV in two-car BEV HHs was 52%, 43%, 41%, 33%, and 33% in Leaf-24, Leaf-30, Bolt-60, Model S-60_80 and Model S-80_100 HHs.

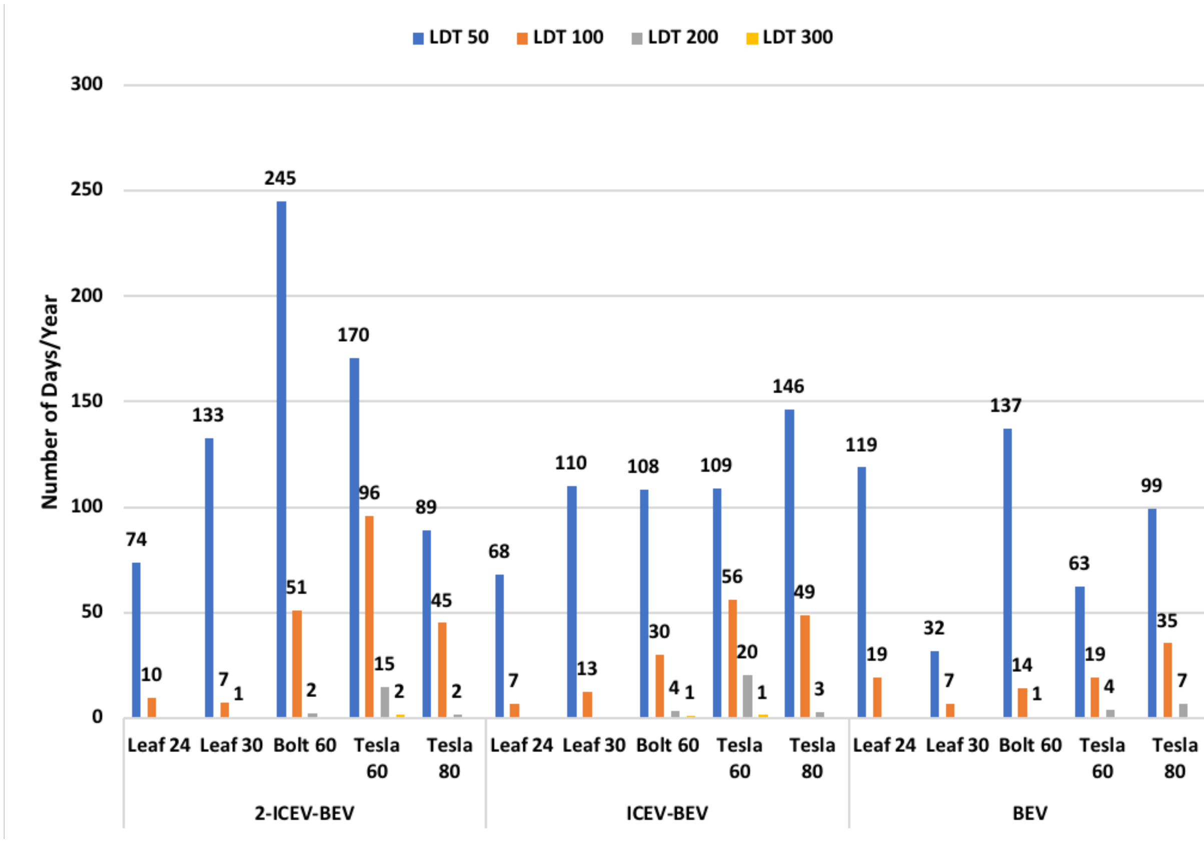


Figure 60. Number of Days/Year BEV was Used for Long Distance Travel (LDT). LDTx: 50-300 or More Miles/Day

Figure 60 shows the absolute number of days per year BEV was used for LDT. In the three-vehicle households, the Bolt-60 was the most used BEV for LDT50, while for the two-vehicle households it was the Model S-80_100, and for single-BEV households it was the Bolt-60. However, the Model S-60_80 was the most used BEV among three-vehicle and two-vehicle households for trips greater than 100 and 200 miles. LDT50 days for Leaf-30 were greater than those for Leaf-24 in three-vehicle and two-vehicle HHs, but the contrary was observed in HHs with just one BEV.

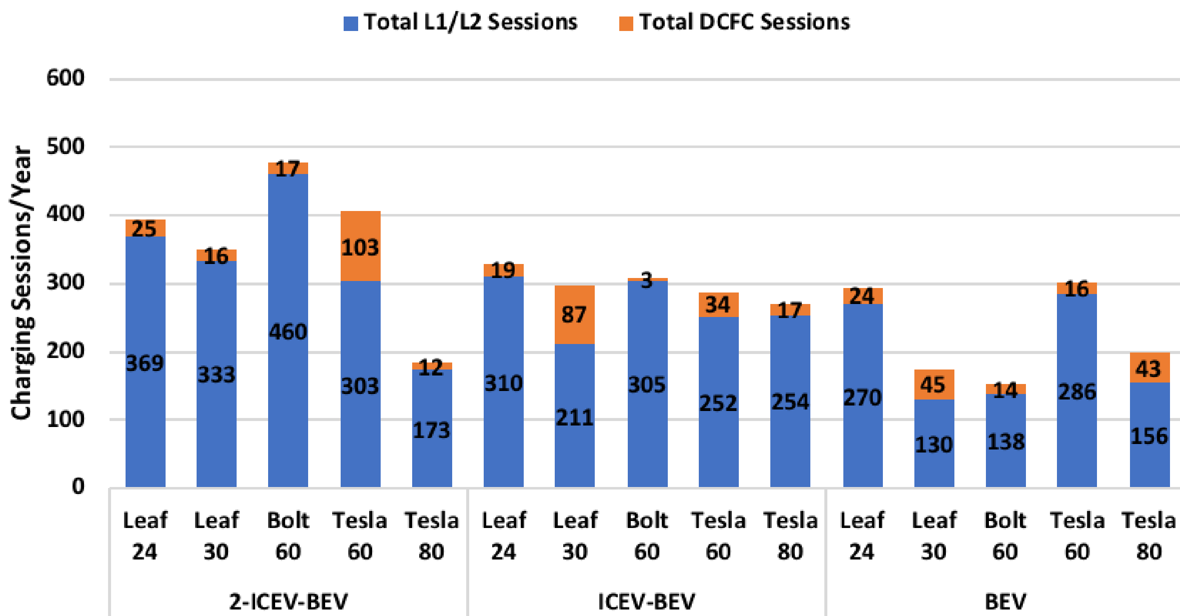


Figure 61. (Average) Annualized Number of L1 or L2 charger (L1/L2), and DCFC Sessions in BEV HHs

Figure 61 shows the average annualized number of L1 or L2 charger and DCFC sessions by BEV type and number of cars in the HH. The Model S-60_80 in three-vehicle HHs used DCFCs the most (103 times per year) followed by the Leaf-30 in two-vehicle HHs (87 times per year). In two-vehicle ICE-BEV(Tesla) households, the BEV was used for commuting in 10 out of the 14 Model S-60_80 cases, and 7 out of the 18 Model S-80_100s cases.

4.2 Households with a PHEV Only or PHEV and ICEV

Analyses and results summarized in **Table 17**–**Table 21** and shown in **Figure 62** – **Figure 66** are based on the logged data. Households with a PHEV only or a PHEV and ICEV have no range limitation on their trips, but have lower potential for eVMT. **Table 17**– **Table 19** summarizes the average annualized estimates of VMT and energy consumption by number of vehicles in the HH and the PHEV type. As a reminder, we recruited only PHEV households that plugged-in their vehicle, which complicates the interpretation of our results in this section.

Table 17. (Average) Annualized Estimates of VMT and Energy Consumption in PHEV HHs by Number of Cars in HH and PHEV Type

HH Type	PHEV Model	PHEV Trip Total	PHEV ZE Only Trips	PHEV CDB/ CS Trips	PHEV CS Only Trips	PHEV VMT Total	PHEV eVMT	PHEV gVMT	PHEV Fuel (gal)	PHEV kWh	ICEV Trips	ICEV VMT	ICEV Fuel (Gal.)
2ICEV -PHEV	Prius Plug-in-4.4	1327	38	642	647	13685	1671	12015	248	-482	2159	28104	958
	C-max/ Fusion-7.6	1269	426	303	541	13353	3463	9890	239	-1058	1930	18283	765
	Volt-16	976	846	70	60	8610	7228	1382	39	-2077	1941	18762	678
ICE-PHEV	Prius Plug-in-4.4	1383	171	745	467	14779	2040	12739	266	-571	906	6422	288
	C-max/ Fusion-7.6	1385	470	464	450	14475	4769	9705	245	-1423	1182	9955	424
	Prius Prime-8.8	1463	704	356	391	14077	5589	8488	162	-1259	1049	8096	368
	Pacifica-16	1485	811	339	314	11599	6295	5304	179	-2464	976	7071	279
	Volt-16	1206	855	210	141	15073	9705	5369	157	-2641	889	7961	350
	Volt-18	1238	980	191	68	11264	7731	3533	95	-2221	1021	8632	356
PHEV	Prius Plug-in-4.4	1298	360	647	291	10851	2354	8497	168	-623	0	0	0
	C-max/ Fusion-7.6	1303	548	400	355	12029	4061	7968	195	-1281	0	0	0
	Prius Prime-8.8	1399	1048	162	189	9754	5706	4049	78	-1268	0	0	0
	Pacifica-16	1707	969	456	262	13734	6004	7730	250	-2412	0	0	0
	Volt -16	1249	977	104	169	10744	6322	4422	129	-1815	0	0	0
	Volt -18	1330	941	284	105	12103	7285	4818	128	-2006	0	0	0

Table 17 shows that in three-car HHs with two ICEVs and one PHEV, the total HH VMT decreased and the average HH UF increased with an increase in the AER of the PHEV. The percentage of HH miles driven in ICEVs was the highest in Volt-16 HHs (69%), followed by Prius Plug-in-4.4 HHs (67%), and C-max/Fusion-7.6 HHs (58%). Annual mileage of ICEVs in C-max/Fusion-7.6 and Volt-16 HHs was almost the same (18,283 and 18,762 miles), but the number of trips and the VMT of the C-max/Fusion-7.6 was higher than those of the Volt-16. **Table 18** collapses the data presented in **Table 17** by household fleet type and utility factor.

In two-car HHs, the percentage of total HH VMT driven using the PHEV was roughly the same in Prius Prime-8.8 and Pacifica HHs (63% and 62%). The average HH UF was higher in Pacifica HHs than in Prius Prime-8.8 HHs (0.35 vs. 0.28) compared to the vehicle's measured utility factor (0.47 vs. 0.51), but the Prius Prime-8.8 had about 2500 miles more than the Pacifica-16 (14,077 miles vs. 11,599 miles), had a lower share of ZE only trips (28% vs. 33%), and charged less often (316 sessions vs. 390 sessions). The Volt-18 has a slightly bigger battery than the Volt 16 and its eVMT was greater than that of the Volt-16 (9,705 miles vs. 7,731 miles), within two-car households. The average household UF did not improve by upgrading from a Volt-16 to a Volt-18 within ICE-PHEV households (0.44 vs. 0.41) or within 1-car single PHEV households (0.62 vs. 0.60). In 2 car HHs, as compared to 1-car single PHEV HHs, the Volt-18 had a lower UF, as did all other PHEV types. To better understand these aspects, we looked at certain key HH level attributes reported by the respondent in the survey; our observations are summarized below for the 2 car (ICE-PHEV) and 1 car (single PHEV) HHs separately.

Volt-16 and Volt-18 in 2-car HHs:

Out of the 22 Volt-16 HHs (ICE-Volt-16 HHs), only 1 was leased, whereas out of the 19 Volt-18 HHs (ICE-Volt-18 HHs) 13 of them were leased. 21 of the 22 Volt-16 HHs reported that they either charged at home only, or home and away in the past 30 days. Out of the 19 Volt-18 HHs, 15 of them reported that they either charged at home only, or home and away in the past 30 days. Only 1 of the Volt-16 HHs reported that they charged away only, whereas this number was slightly higher in Volt-18 HHs, where 4 of them reported that they charged away only. The average number of drivers in both the Volt-16 and Volt-18 HHs was comparable (2.1 vs. 2). The average HH size of Volt-18 HHs was slightly higher (3) compared to the average HH size of Volt-16 HHs (2.36). 70% of the Volt-16 (16 out of the 22) and 90% of the Volt-18 (17 out of the 19) were used by HH members working full-time for commuting purposes.

Despite the longer range of the Volt-18 compared to the Volt-16, the ICE was probably used more often due to the HH size. Since the Volt-16 was the first ever mass-produced series type PHEV, higher annual VMT of Volt-16 in two car HHs could also be because these were driven by early adopter technology enthusiasts who were also innovators. Furthermore, the smaller HH size and lower share of Volt-16 being leased and charging exclusively away as compared to Volt-18 are the other reasons for the difference in usage between Volt-16 and Volt-18 in 2 car HHs (ICE-PHEV HHs).

Volt-16 and Volt-18 in 1-car HHs:

9 out of 12 Volt-16 were purchased, whereas only 5 of out of 14 Volt-18 were purchased. The higher annual VMT of Volt-18 compared to Volt-16 can be primarily attributed to the higher share of drivers in Volt-18 HHs who used it for commute purposes.

Table 18. (Average) Annualized Estimates of PHEV VMT, HH VMT, and HH UF

HH Type	PHEV Type	Number of HHs	PHEV eVMT	HH VMT	UF
2ICEV-PHEV	Prius Plug-in-4.4	2	1671	41789	0.04
	C-max/Fusion-7.6	6	3463	31635	0.12
	Volt-16	4	7228	27373	0.27
ICE-PHEV	Prius Plug-in-4.4	12	2040	21201	0.11
	C-max/Fusion-7.6	24	4769	24430	0.22
	Prius Prime-8.8	17	5589	22173	0.28
	Pacifica-16	18	6295	18670	0.35
	Volt-16	22	9705	23034	0.44
	Volt-18	18	7731	19897	0.41
PHEV	Prius Plug-in-4.4	5	2354	10851	0.25
	C-max/Fusion-7.6	16	4061	12029	0.36
	Prius Prime-8.8	8	5706	9754	0.62
	Pacifica-16	7	6004	13734	0.47
	Volt-16	12	6322	10744	0.62
	Volt-18	15	7285	12103	0.60

Table 19 summarizes the average annualized estimates of PHEV charging needs by number of cars in the HH and the PHEV type and **Table 20** summarizes the average daily estimates of PHEV charging by PHEV type.

Table 19. (Average) Annualized Estimates of Number of Charging Sessions and kWh Charged in PHEV HHs by Number of Vehicles and PHEV Type

HH Type	PHEV Type	Annualized Charging Sessions	Annualized Charging kWh	Average Charging Duration/Session (minutes)	Average kWh/ Session
2ICEV-PHEV	Prius Plug-in-4.4	272	658	112	3
	C-max /Fusion-7.6	218	956	270	5
	Volt-16	379	2085	223	7
ICE-PHEV	Prius Plug-in-4.4	350	812	118	3
	C-max /Fusion-7.6	401	1458	204	4
	Prius Prime-8.8	316	1168	217	4
	Pacifica-16	390	3023	323	10
	Volt-16	393	2612	331	8
	Volt-18	287	2131	281	8
PHEV	Prius Plug-in-4.4	410	874	105	2
	C-max /Fusion-7.6	380	1309	178	4
	Prius Prime-8.8	410	1213	159	3
	Pacifica-16	541	2997	109	8
	Volt-16	328	1784	326	6
	Volt-18	249	1962	344	9

Table 20. (Average) Annualized Estimates of Charging Sessions by PHEV Type in PHEV HHs

Average Annual	PHEV	Charging Sessions/Year	Charging Energy kWh/Year
	Prius Plug-in-4.4	357	812
	C-max/Fusion-7.6	370	1341
	Prius Prime-8.8	346	1183
	Pacifica-16	433	3016
	Volt-16	371	2295
	Volt-18	270	2054
Average Daily	**PHEV**	**Charging Sessions/Day**	**kWh/Day**
	Prius Plug-in-4.4	0.984	2.23
	C-max/Fusion-7.6	1.040	3.73
	Prius Prime-8.8	0.950	3.24
	Pacifica-16	1.108	8.28
	Volt-16	1.018	6.32
	Volt-18	0.740	5.63

Figure 62–**Figure 64** depict the HH UF from four different perspectives calculated using the logged data: individual HH level UF by number of vehicles in the HH and PHEV type, average HH UF by PHEV type, and average HH UF by number of vehicles in the HH and PHEV type.

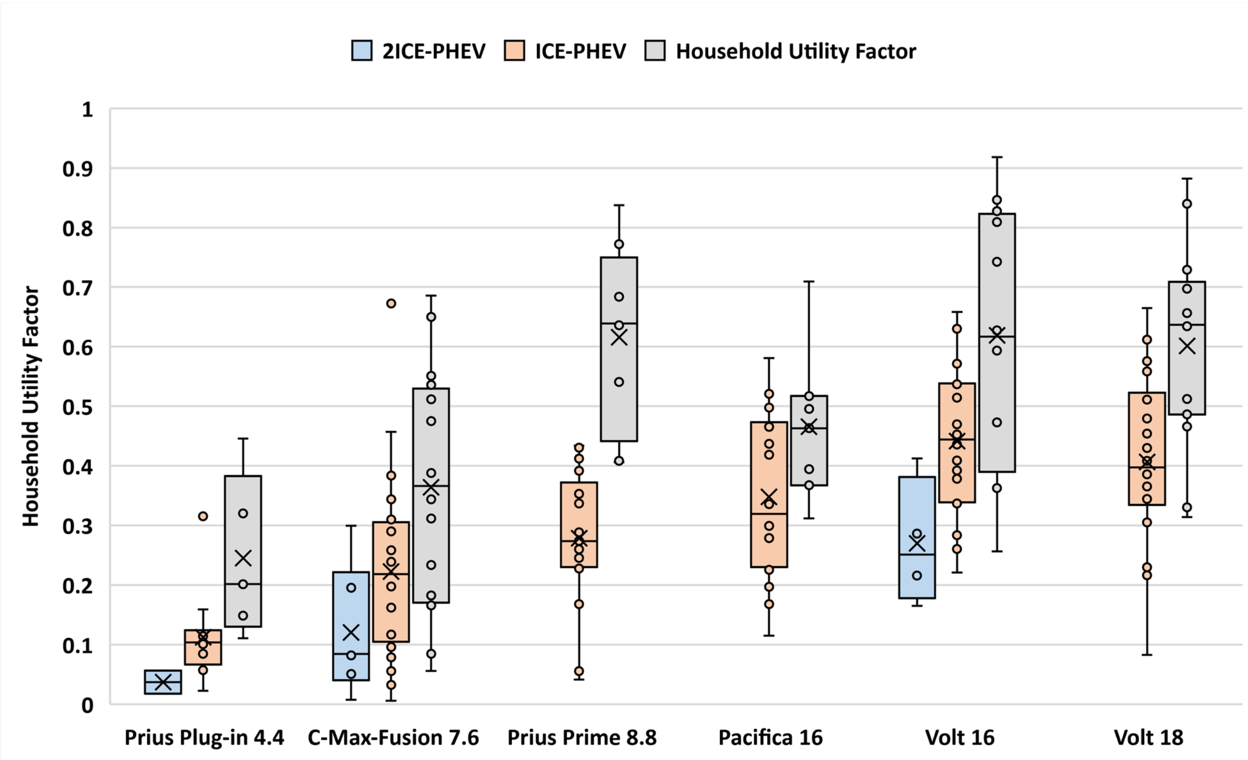


Figure 62. Individual HH UF by PHEV Type in PHEV HH

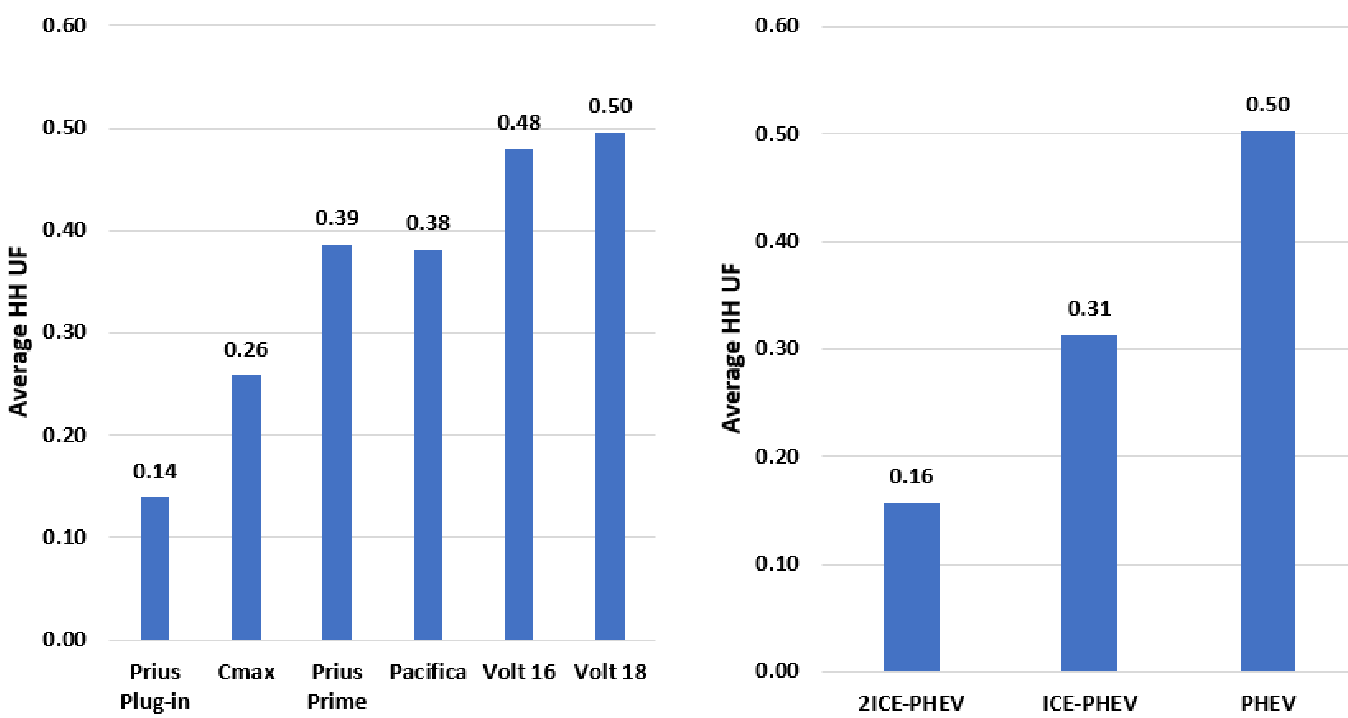


Figure 63. Average HH UF by PHEV Type (Left: all HHs); and Average HH UF by Number of Cars in the HH (Right: all PHEVs)

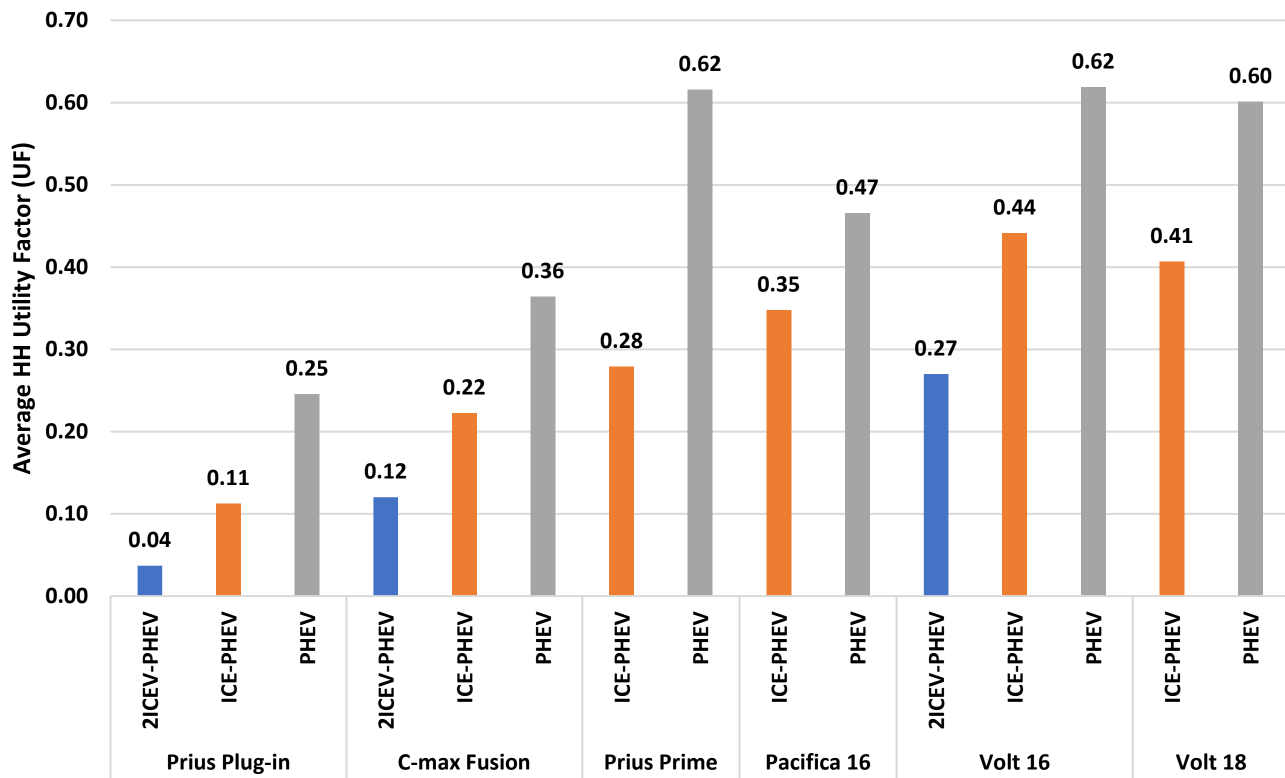


Figure 64. Average HH UF by Number of Cars per HH and PHEV Type

Table 21. Average Utility Factor (UF) of PHEVs by Model Year (MY) According to the EPA Dataset

PHEV	MY	City EPA Fuel Economy UF	Highway EPA Fuel Economy UF	Combined EPA Fuel Economy UF	CARB Midterm Report
Prius Plug-in-4.4	2012-2014	0.320	0.250	0.290	0.15
C-max/Fusion-7.6	2013-2017	0.481	0.421	0.455	0.32
Prius Prime-8.8	2017	0.553	0.498	0.529	N/A
Pacifica-16	2017-2018	0.640	0.586	0.617	N/A
Volt-16	2011-2015	0.664	0.642	0.652	0.6
Volt-18	2016-2017	0.778	0.737	0.761	0.6

Table 21 shows the average UF of PHEVs by different model years that are in the logged vehicle dataset from the EPA. The UF based on the CARB Midterm Review (CARB 2017b, 2017a) is also added to **Table 21** for comparison purposes. Overall, the EPA UFs are higher than the CARB Midterm Review (MTR) UFs

and the UC Davis values calculated from the logger data. UFs of logged PHEVs from single PHEV HHs are closer to the CARB MTR UFs except in the case of the Prius Plug-in-4.4 UF.

The interpretation of UFs varies noticeably by level of aggregation (vehicle or household level) and the number of vehicles in the household. In addition, the marginal improvements in upgrading from Volt-16 to Volt-18 were negligible in one-car HHs and two-car HHs. If we ignore the context of the HH (**Figure 63**, left), we find that the fleet average UFs of PHEVs in our study were lower than the CARB MTR UFs by 0.01-0.12, depending on the PHEV type.

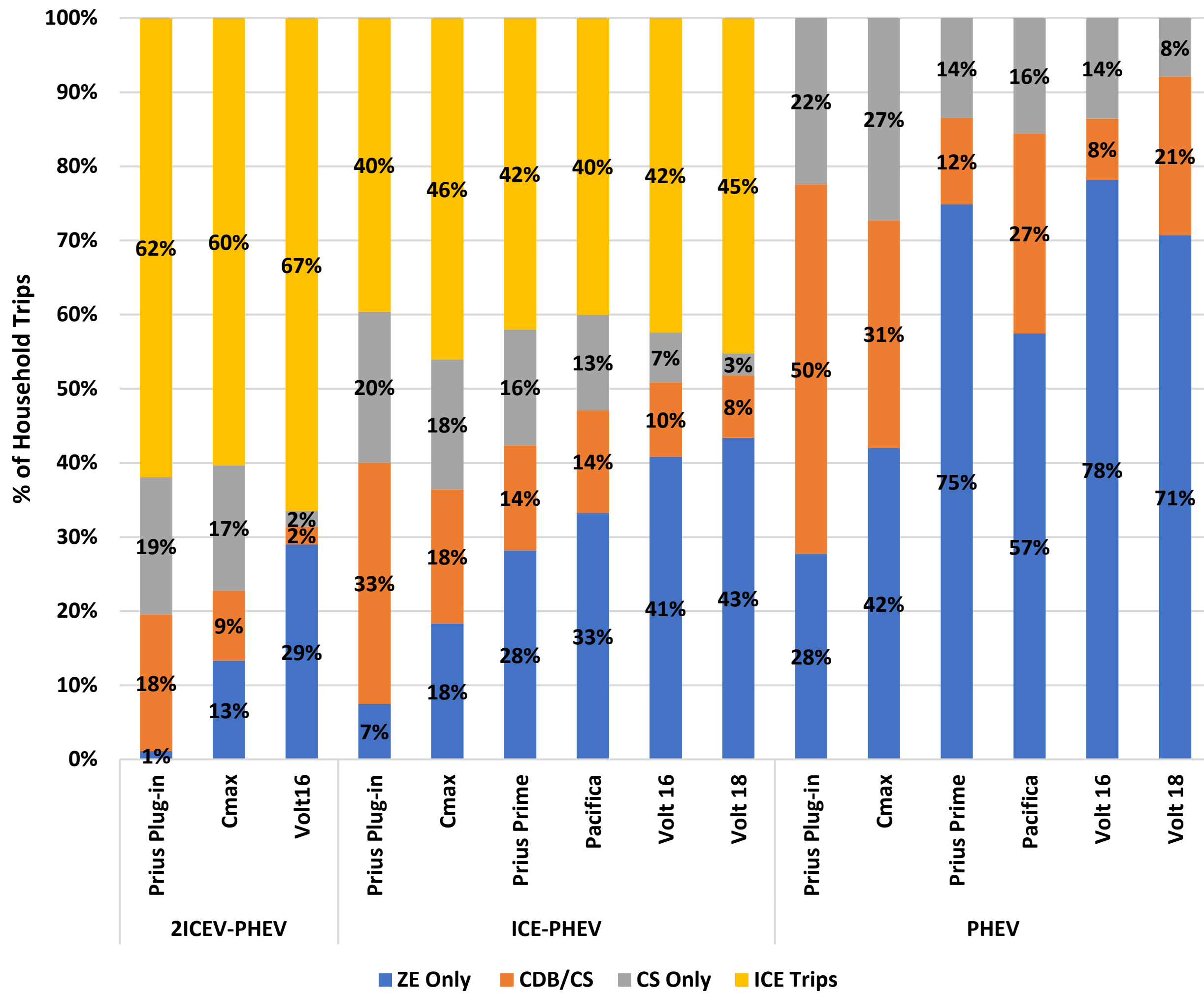


Figure 65. Percentage of Household Trips Powered by Different PHEV Driving Modes or ICEVs

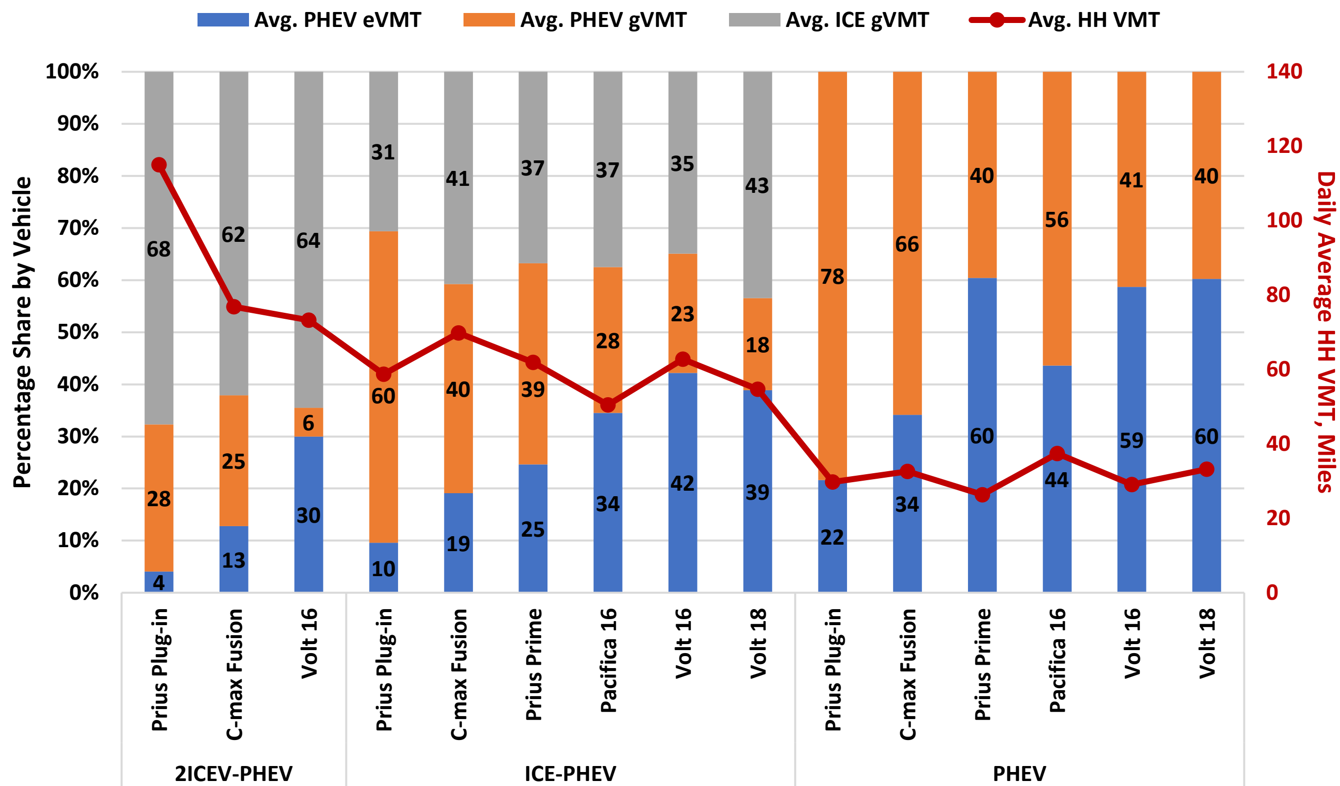


Figure 66. Daily Average HH VMT and Percentage Share of PHEV eVMT, PHEV gVMT, and ICE gVMT

Figure 66 shows the average daily HH VMT and percentage share of eVMT and gVMT. This figure demonstrates that the average daily HH VMT of C-max/Fusion-7.6 HHs did not change much between three car HHs and two car HHs. Daily eVMT of Pacifica-16 was similar in two car and single car HHs (within 10 miles). On average, the daily HH VMT of Volt-16 HHs was lower than that of C-max/Fusion-7.6 HHs in one car, two car, and three car HHs.

4.3 Two-PEV Households: BEV and PHEV Mix

In the following section we present data from households with two PEVs. The sample size is only 11 households and, even though the total number of days and miles is high, the analysis cannot be generalized to the population of PEV users. Analyses and results presented in **Table 22**– **Table 24** and depicted in **Figure 67**– **Figure 69** are based on the logger data.

Table 22. Double-PEV (1 BEV and 1 PHEV) HHs With or Without ICEV(s) (N=9)

Type of HH	BEV, PHEV in the HH	Number of HHs
ICE-BEV-PHEV	Leaf-24-C-Max/Fusion-7.6	2
ICE-BEV-PHEV	RAV4 EV-42-Volt-16	1
ICE-BEV-PHEV	RAV4 EV-42-C-Max/Fusion-7.6	1

Type of HH	BEV, PHEV in the HH	Number of HHs
BEV-PHEV	Leaf-24-C-Max/Fusion-7.6	1
BEV-PHEV	Model S-60_80-Pacifica-16	1
BEV-PHEV	Bolt-60-Prius Prime-8.8	1
BEV-PHEV	RAV4 EV-42-Prius Plug-in-4.4	1
BEV-PHEV	Leaf-24-Volt-16	1
BEV-PHEV	Model S-60_80-Volt-16	1
BEV-PHEV	Leaf-30-Volt-18	1

4.3.1 Households with a BEV and a PHEV

As shown in **Figure 67** and **Figure 68**, the average household VMT of Leaf-30-Volt-18 HHs was lowest but had the highest UF compared to all other BEV-PHEV HHs.

The average annualized estimates of other metrics in BEV-PHEV HHs are summarized below in **Table 23** and **Table 24**.

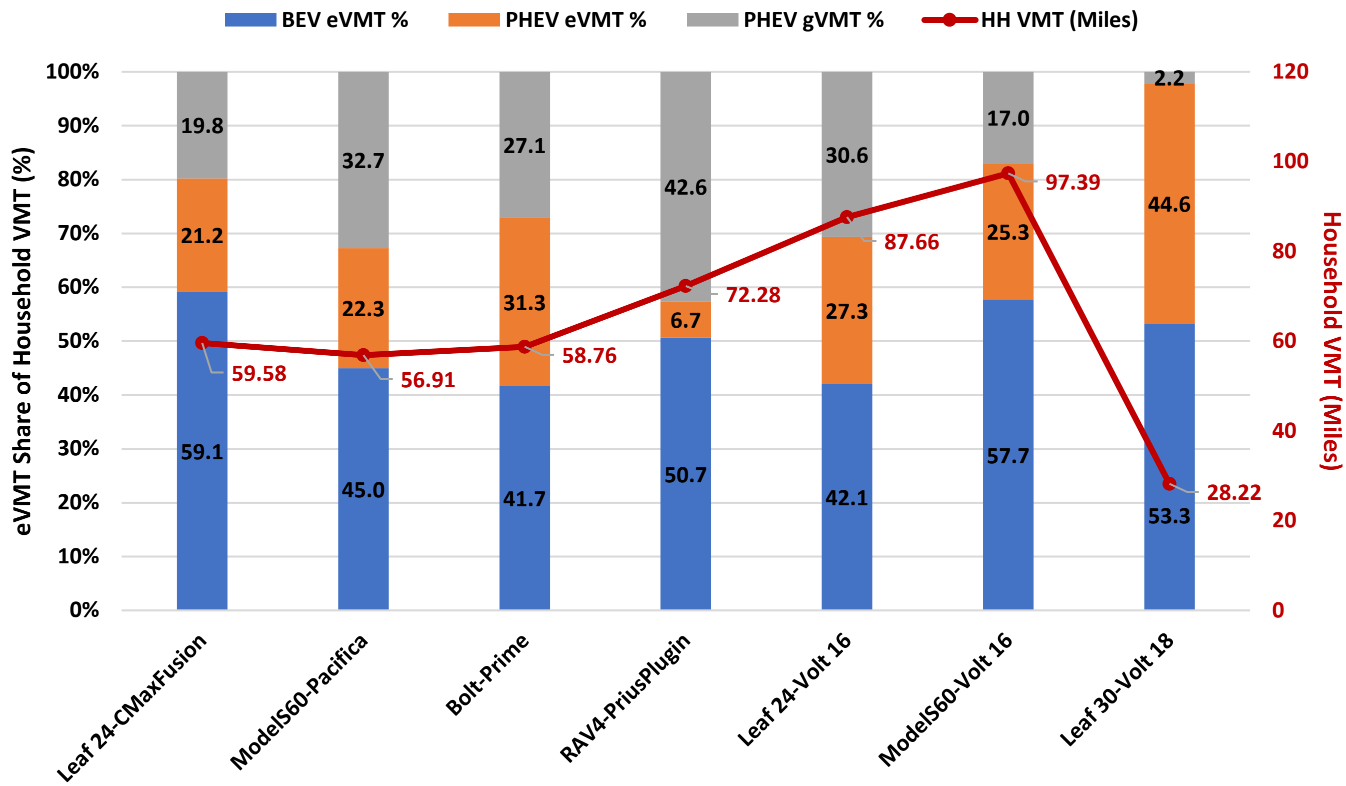


Figure 67. Daily Average HH VMT, and Percentage of eVMT and gVMT BEV-PHEV Households

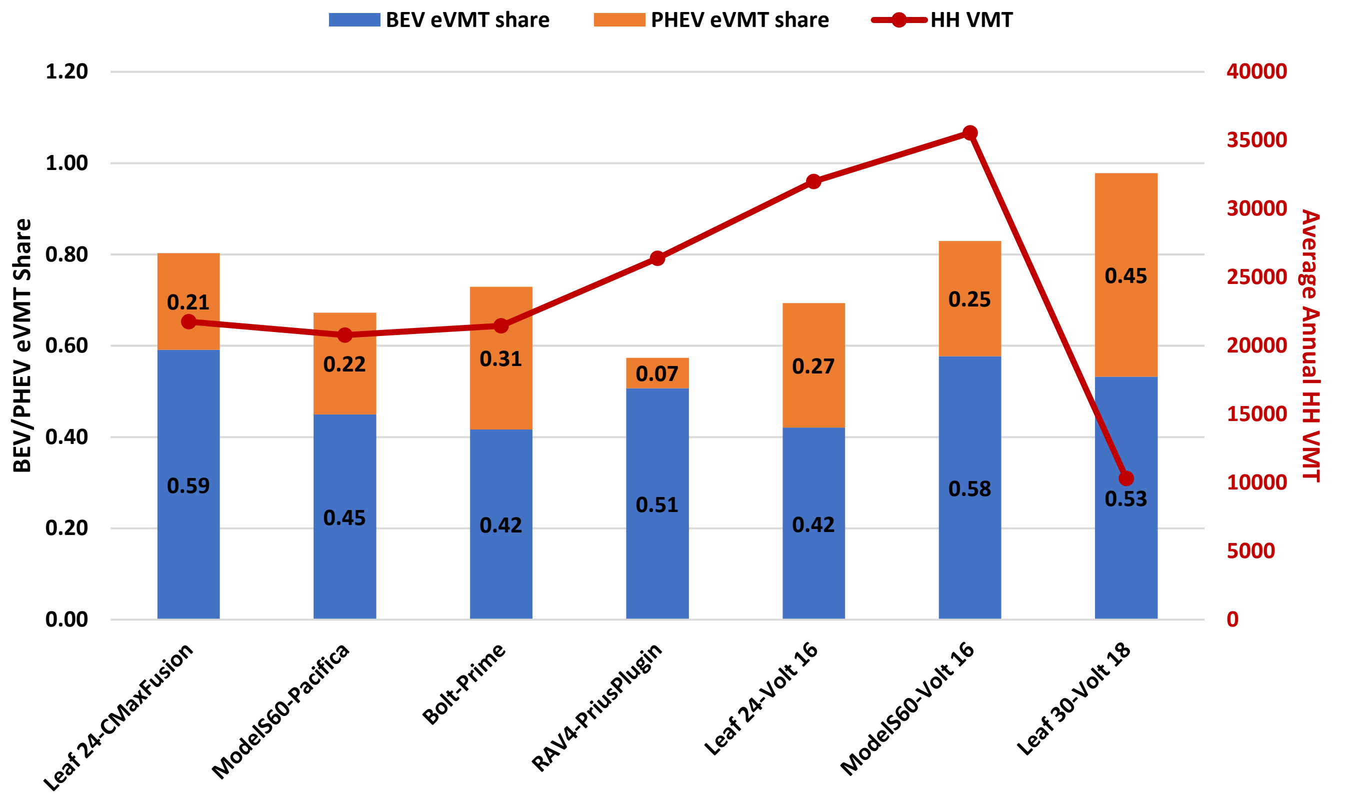


Figure 68. Average Annual HH VMT and Share of BEV eVMT and PHEV eVMT in BEV-PHEV HHs

Table 23. Annualized Driving Metrics in BEV/PHEV HHs

BEV-PHEV	PHEV eVMT	BEV eVMT	PHEV gVMT	HH VMT	HH UF	PHEV Fuel (gal)	PHEV Driving Energy (kWh)	BEV Driving Energy (kWh)
Leaf-24-CMax/Fusion-7.6	4601	12851	4296	21748	0.802	113	-1497	-3317
Model S-60_80-Pacifica-16	4632	9337	6801	20771	0.673	86	-704	-1128
Bolt-60-Prius Prime-8.8	6706	8937	5806	21449	0.729	78	-1269	-2089
RAV4 EV-42-Prius Plug in-4.4	1772	13368	11242	26382	0.574	258	-585	-5379
Leaf-24-Volt-16	8741	13454	9801	31996	0.694	261	-2608	-3350
Model S-60_80-Volt-16	8985	20507	6054	35546	0.830	189	-2806	-6342
Leaf-30-Volt-18	4592	5485	224	10300	0.978	7	-1496	-1674

Table 24. Annualized Charging Metrics in BEV/PHEV HHs

BEV-PHEV	PHEV Total Sessions	PHEV Total Charging kWh	BEV Total Sessions	BEV Total Charging kWh	BEV DCFC Sessions
Leaf-24-CMaxFusion	470	1620	484	3217	0.0
Model S 60_80-Pacifica-16	257	1525	226	3288	2.6
Bolt-60-Prime	321	1381	133	2537	0.0
RAV4 EV-42-Prius Plug-in-4.4	278	749	343	4823	0.0
Leaf-24-Volt-16	393	2647	381	3346	4.0
Model S 60_80-Volt-16	361	2858	275	6832	33.0
Leaf-30-Volt-18	230	1372	183	1276	0.0

4.4 UF and GHG Profile

In this section, we focus on the utility factors and GHG emissions of the PEVs and the household fleets using the logger data. Of the total 303 HHs, we use a subset of HHs with one PEV and one ICE, exclude households with one vehicle and households with more than two vehicles, and we analyze the disparities in vehicle level and household level UF and GHG emissions. The UF and GHG profile of the 183 two car households (72 HHs with ICE-BEV and 111 HHs with ICE-PHEV) is analyzed using the average annualized estimates of the relevant PEV usage metrics by PEV type covered in Sections 4.1-4.2. For parity purposes, we restrict this analysis to only two car HHs with single ICE and single PHEV or BEV. Since the logged HHs are PEV early adopter HHs, the ICEs in these HHs are not representative of general population of ICE owners. The well to wheel emissions factors for electricity and gasoline are 378.54 gCO2e/kWh and 11405.85 gCO2e/Gallon of gasoline.(CARB 2017c)

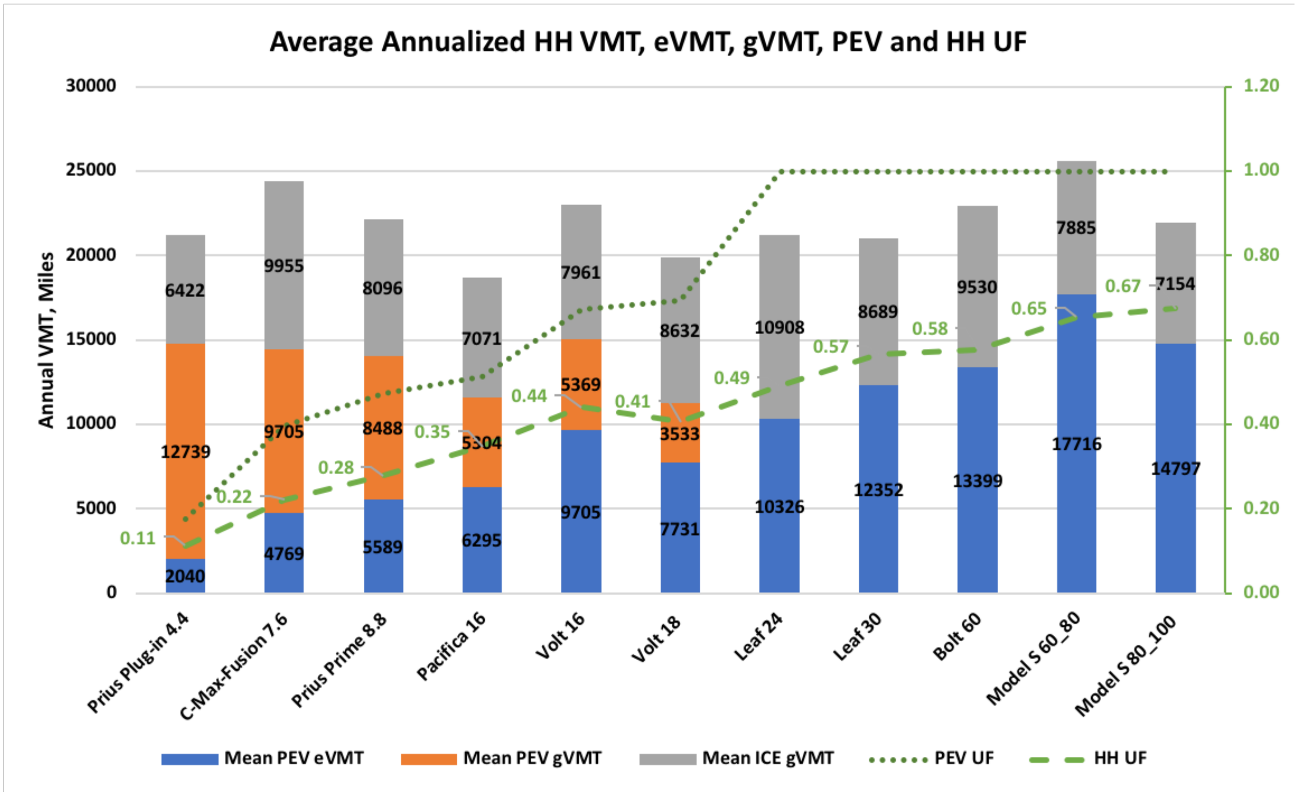


Figure 69. Two car HHs VMT by Vehicle Type, PEV UF and HH UF

Figure 69 presents the VMT of ICE-PEV HHs by PEV type, fuel source, PEV UF, and HH UF. The total annual miles of these households range between 18,700 for the Pacifica-16 and 25,600 for the Tesla Model S-60_80, but, apart from Volt-18 HHs, the HH utility factor is always increasing with the PEV range. For short range PHEVs, the household utility factor is just over half of the PEV utility factor. For the Volts, the PHEVs electrify about 40% of the household miles. The longer range BEVs electrify around 60% to 70% of the household VMT partly because of lower miles for the ICEV in long-range Tesla HHs.

Figure 70 presents the average GHG per mile for the PEVs in the studied fleet. As expected, the short-range BEVs have the best performance followed by the larger battery capacity BEVs and the PHEVs. We see that the relatively gas-efficient engine on PHEVs results in GHG emissions not much higher than larger battery vehicles. The results are based on average electricity derived GHG described above and on the logged travel behavior.

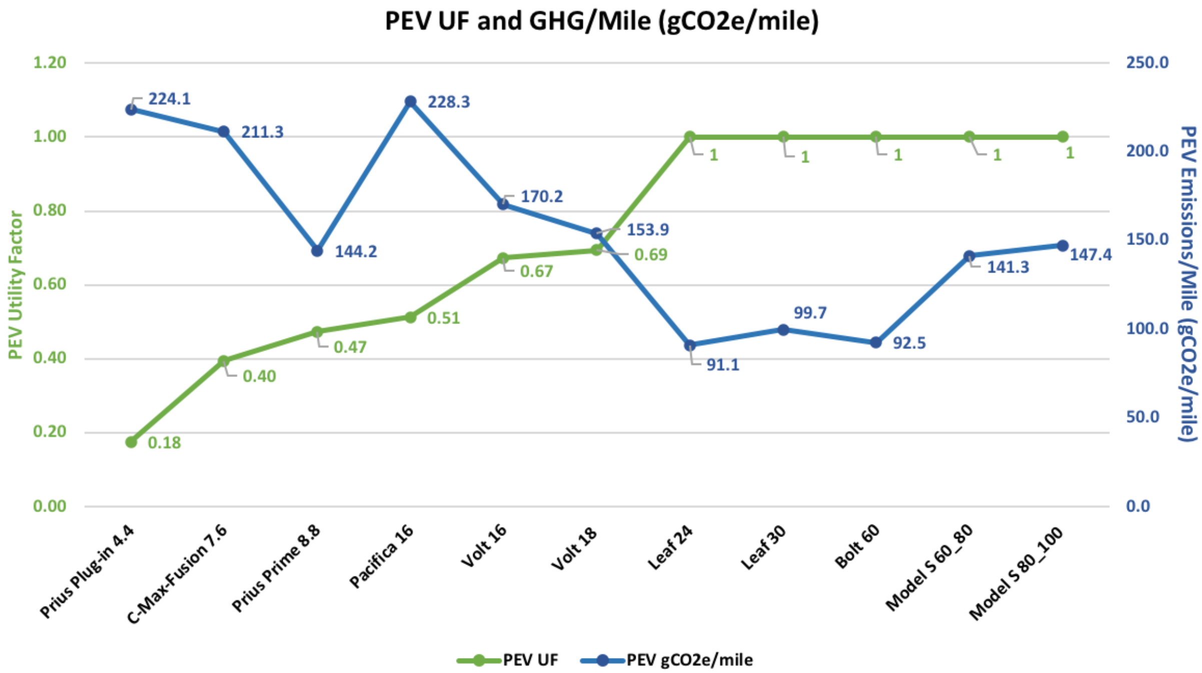


Figure 70. Average GHG per Mile and Utility Factor

Figure 71 has the household level (PEV+ICEV households) GHG sources in comparison to the GHG per mile from energy (gas and electricity) consumed by the PEVs and from gasoline consumed by the ICEV in two vehicle households. We also include the household utility factor (HH eVMT/VMT).

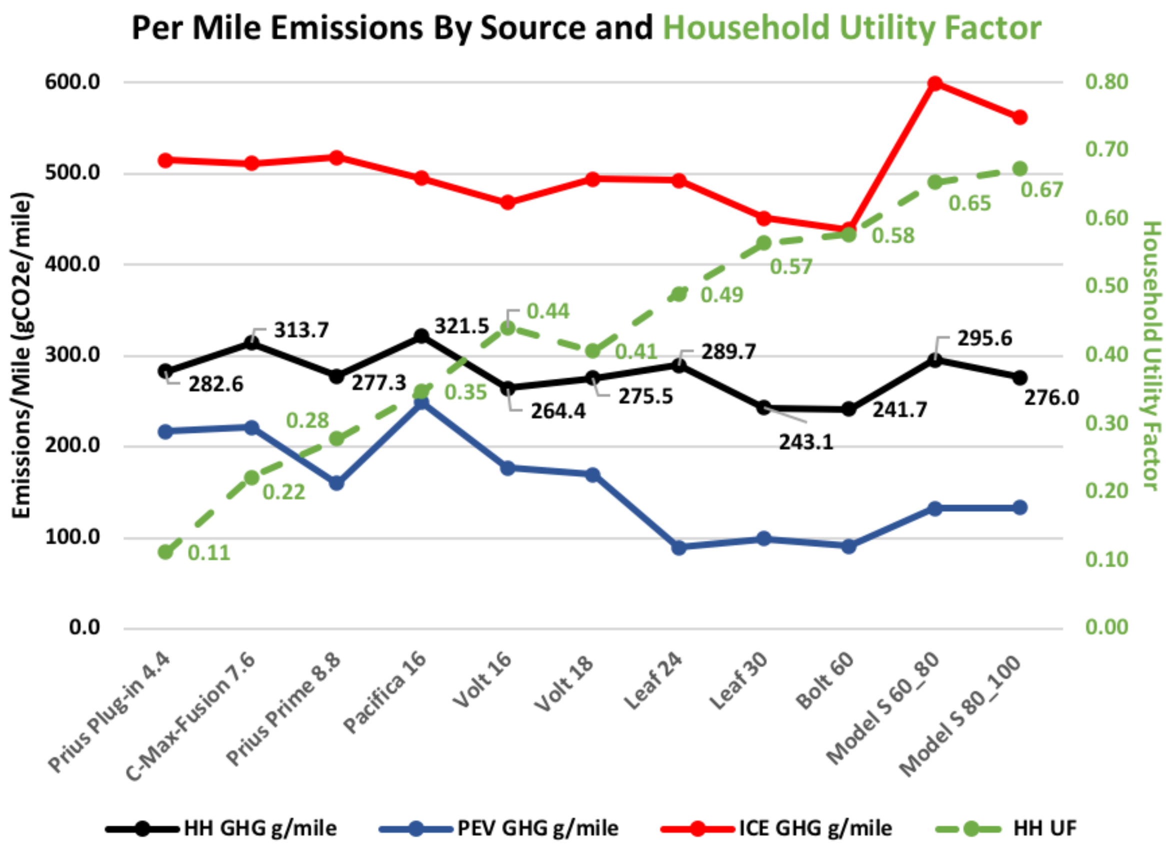


Figure 71. Household Level GHG and Utility Factor per Mile

The actual performance of each household depends on the metric considered. At the household level, the total VMT and ICE VMT substituted with PEV eVMT are the major determinants of the HH UF. From an emissions perspective, in addition to the aforementioned factors, it is also important to account for not just the quantity of ICE VMT substituted but also the quality. The disparities in HH GHG/mile between HHs with different PEVs is therefore influenced by (1) energy and carbon intensity of ICE; (2) usage intensity of the ICE (absolute VMT); (3) energy intensity (kWh/mile) of the PEV and its charging related emissions; (4) battery capacity of the PEV which directly impacts the eVMT; (5) CDB or CS mode miles and gasoline consumption in PHEV HHs. **Figure 69**, **Figure 71**, and **Figure 72**, when analyzed together, present a complete picture of HH level emission impacts of PEVs for a two-vehicle household.

The mean ICE gVMT in Tesla HHs is between 7000-8000 miles, whereas in the Leaf HHs, it is between 8000-11000 miles. Leaf-30 HHs have lower HH GHG/mile compared to Leaf-24 HHs because of its bigger battery. The incremental eVMT enabled is also due to the bigger battery of the Leaf-30, which overcompensates for the fact that ICEs in Leaf-30 HHs are less efficient compared to the ones in Leaf-24 HHs (445 gCO2e/mile compared to 415 gCO2e/mile).

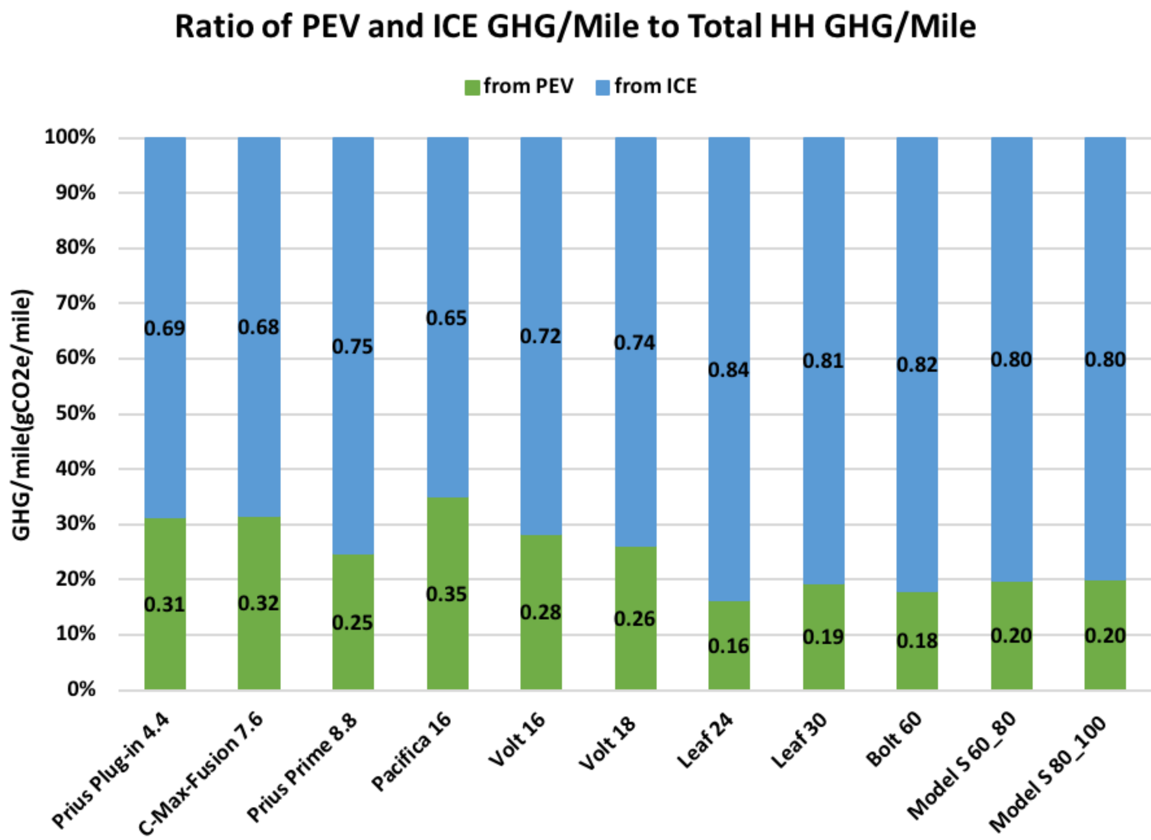


Figure 72. Ratio of PEV and ICE GHG/Mile to Total HH GHG/Mile

The ICEs in Model S-60_80 HHs are the most inefficient (599 gCO2e/mile) but have the fourth lowest ICE usage intensity on an absolute VMT basis, and thereby the second highest HH UF. However, on a per mile HH GHG/mile it performs best among the rest of PEV types simply because of its lower ICE usage intensity. In contrast, the ICE in Model S-60_80 HHs has a higher usage intensity on an absolute VMT basis when compared to the ICE in Tesla Model S-80_100 HHs. The ICE GHG/mile in Tesla Model S-80_100 HHs was only 6% lower (561 gCO2e/mile vs. 599 gCO2e/mile) when compared to ICE in Tesla Model S-60_80 HHs, but the usage intensity of ICE in Model S-60_80 HHs was 10% higher than those in Model S-80_100 HHs (7885 miles vs 7154 miles).

The Leaf HHs on the other hand have a higher ICE usage intensity compared to the Model S HHs on an absolute VMT basis, which is the reason for Leaf HHs having lower UF compared to the UF of Model S HHs. On average, the ICEs in Bolt-60 HHs are about 15% more efficient than the ICEs in the Model S HHs (both 60-80 and 80-100 kWh) on a gCO2e/mile basis and this causes the overall HH GHG/mile in Bolt-60 HHs to be lower than that of the Model S HHs.

Three factors cumulatively work in favor of the Bolt-60 HH to have the lowest HH GHG/mile compared to other BEV HHs: lower ICE usage intensity compared to Leaf-24 HHs, lower energy intensity of the PEV and carbon intensity of the ICE compared to Model S HHs. When we look at the PHEV HHs, Volt-16 HHs have the lowest HH GHG/mile. Though the UF of Volt-16 HH was similar to that of the Volt-18 HH, the Volt-18 HH GHG/mile is higher. This is because the ICEs in Volt-18 HHs have higher usage intensity. Referring to Fig. 83, we can clearly see that on a GHG/mile basis, the only distinguishing aspect between

Volt-16 and Volt-18 HHs is the ICE usage intensity. Prius Prime-8.8 HHs have the highest ICE usage intensity among PHEV HHs and C-Max/Fusion-7.6 HHs have the highest HH GHG/mile across all PEV HHs.

The HH GHG/mile (blackline in the middle of **Figure 71**) shifts upwards if the ICE usage intensity and ICE carbon intensity increases. As far as determining how the curve would shift, we must consider the carbon, energy, and usage intensity of the ICE and PEVs. If we ignore the specific ICE class/segment (compact, SUV, sedan etc.), ICE carbon intensity increases with the AER in BEV HHs. The reverse of this trend can be observed as we move (left to right) from C-max/Fusion-7.6 HHs up to Volt-18 HHs. Long-range BEV HHs (Model S HHs) on average have higher emissions from the ICE on a per-mile basis compared to all other PEVs.

4.5 Additional ICE Usage Metrics

We briefly summarize usage metrics of the ICE in PEV HHs using the average annualized estimates summarized in **Table 16** - **Table 24** based on the logger data. For clarity, the ICE usage summaries of 2 car HHs and 3 car HHs are presented separately. In the case of 3 car HHs (2 ICEs and 1 BEV or PHEV), the total ICE VMT is considered. Due to a low sample size of HHs with single ICE and more than 1 PEV (4 HHs) and HHs with two PEVs (7 BEV-PHEV HHs), we have excluded them, therefore the sub-sample of HHs considered is 207. Overall, among the logged households, the average fuel economy of the ICE was 23.89 mpg and the average model year was 2010.

4.5.1 Average Annual ICE VMT

Figure 69 depicts the average annualized ICE VMT in 2 car HHs with one PEV and one ICE. In most cases, the ICE vehicle in a mixed PEV-ICEV household is used less than the average vehicle in California and less than the plug-in vehicle in the household.

Referring to **Figure 73,** we notice a steady decline in the annual ICE VMT in BEV HHs with increase in range/battery capacity in 2 car HHs, except for 2 car Leaf-30 HHs. In the case of PHEV HHs, the annual ICE VMT exhibited a variation. ICEs in Prius Plug-in-4.4 HHs drove the least among the 2 car PHEV HHs and was even lower than the ICE VMT in 2 car Model S-80_100 HHs.

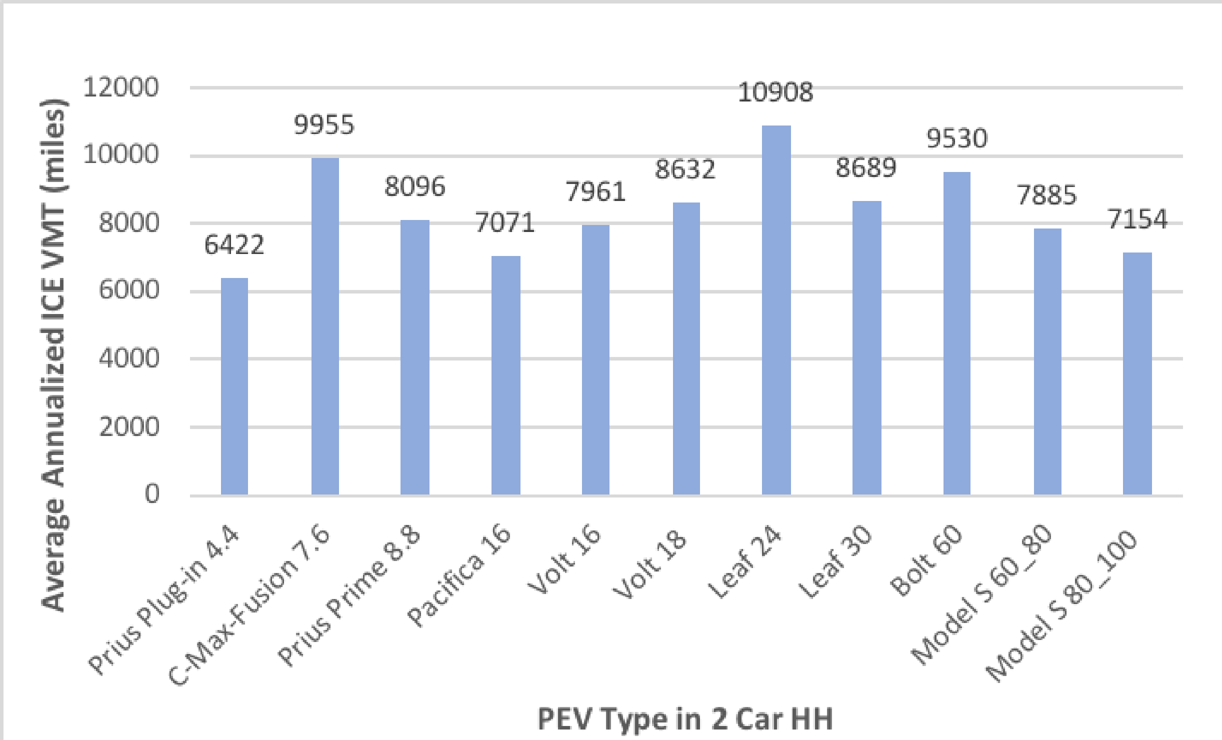


Figure 73. Average Annualized ICE VMT in 2 Car HHs (Single ICE and Single PHEV or BEV) by PEV Type. N=183 HHs

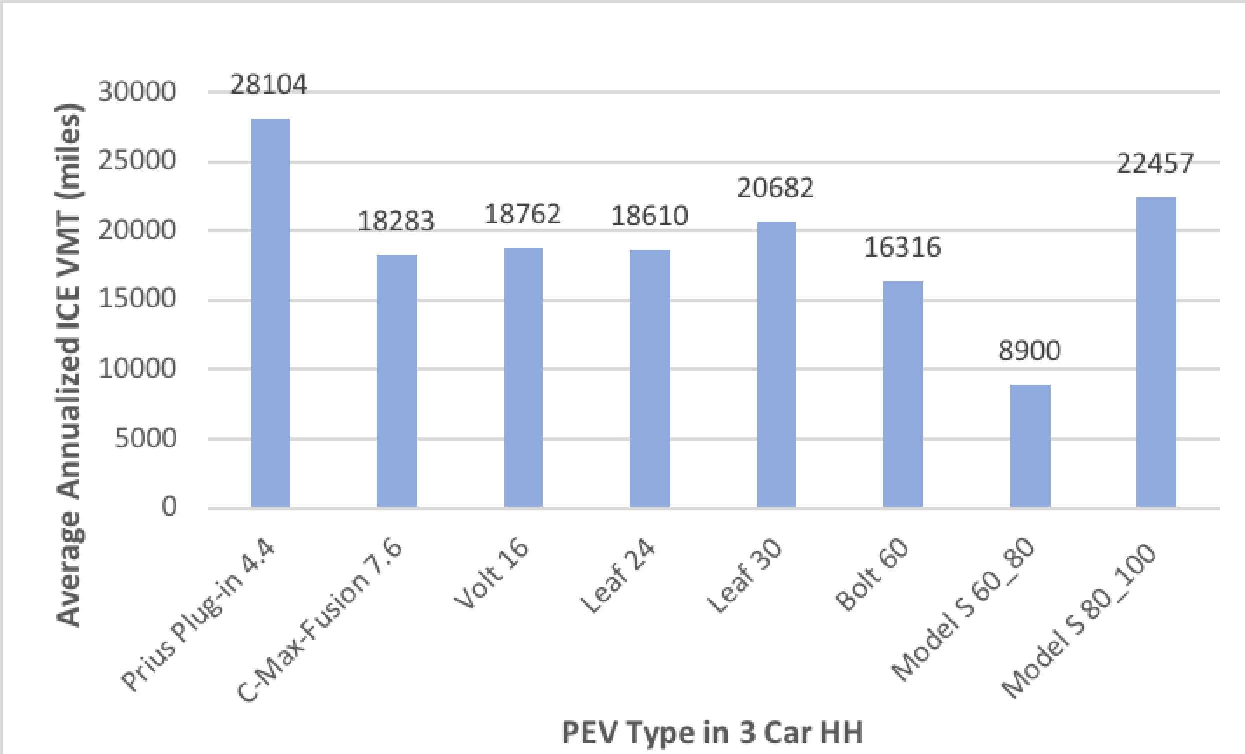


Figure 74. Average Annualized ICE VMT in 3 Car HHs (Two ICEs and Single PHEV or BEV) by PEV Type. N=24 HHs.

Referring to **Figure 74**, there was considerable variation in annual ICE VMT of 3 car HHs across all PEV types. The ICEs in 3 car Prius Plug-in-4.4 HHs had the highest annual ICE VMT followed by Model S-80_100 HHs and the ICE VMT in Leaf-30 HHs.

4.5.2 ICE Usage for Long Distance Travel (LDT)

We characterized long distance travel (LDT) using two daily VMT thresholds, 50 miles and 100 miles (LDT50 and LDT100). **Figure 75** and **Figure 76** depict the average annualized number of days per year the PEV and ICE was used for LDT50 and LDT100 in 2 car PHEV and 2 car BEV HHs, respectively. The ICE share (%) of total HH LDT50/100 days is shown using the secondary Y axis in **Figure 75** and **Figure 76.**

Referring to **Figure 75,** in 2 car ICE-PHEV HHs, the ICE share of total HH LDT50 days per year was lowest for Volt-16 HHs (22%), whereas the ICE share of total HH LDT100 days per year was lowest for Prius Plug in 4.4 HHs (27%). The ICE usage for LDT50 and LDT100 in Prius Plug-in-4.4 HH were comparable on a percentage share of the HH LDT50(100) days/year and a similar trend was observed in Volt-18 HHs and Pacifica-16 HHs. The ICE in 2 car Volt-16 HHs was used roughly on 15% more days for LDT100(38%) compared to LDT50(22%).

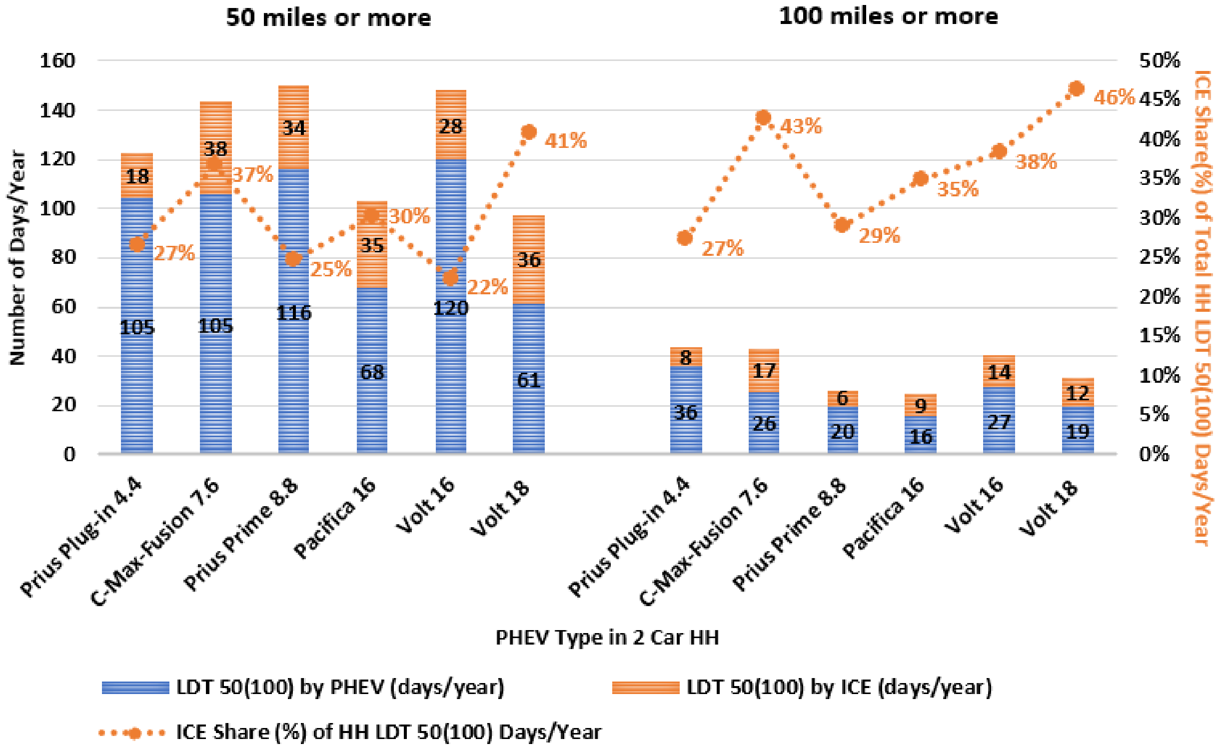


Figure 75. PHEV and ICE Use (Days/Year) for Long Distance Travel 50(100) Miles or More in 2 Car HHs (Single ICE and Single PHEV); ICE Share (%) Total HH LDT50(100) days/year shown on the secondary Y axis. N=77 HHs.

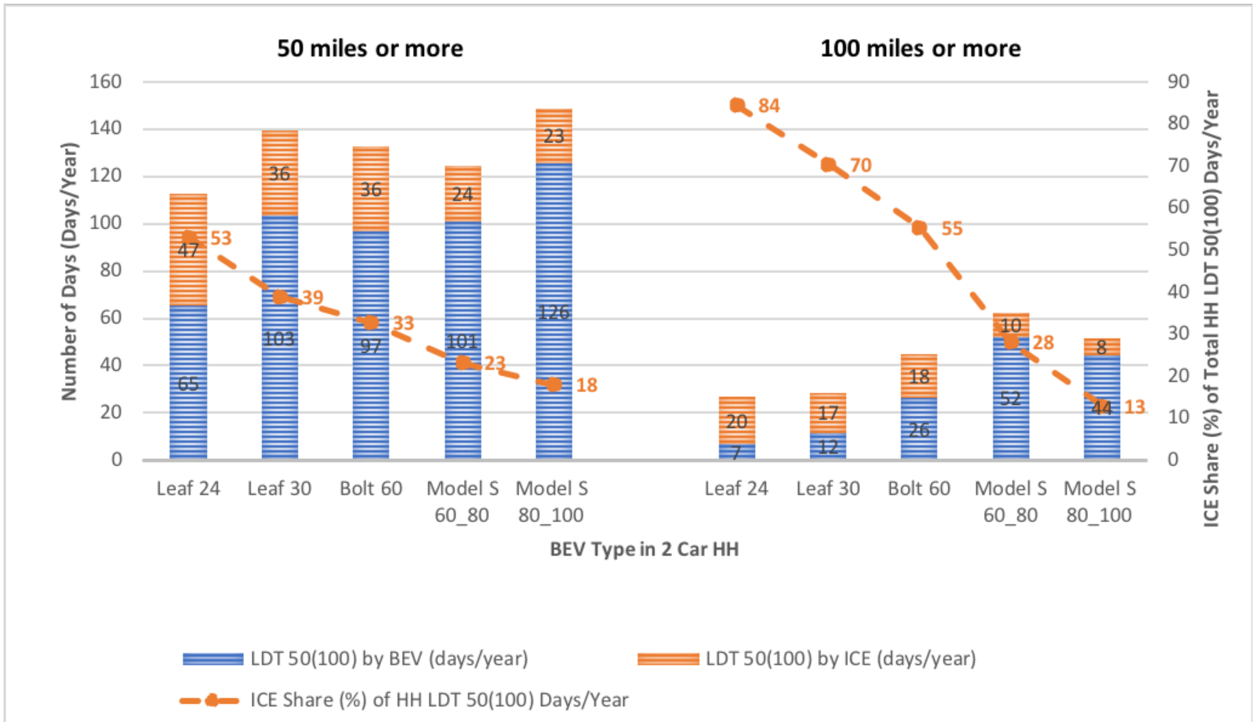


Figure 76. BEV and ICE Use (Days/Year) for Long Distance Travel 50(100) in 2 Car HHs (Single ICE and Single BEV); ICE Share (%) of Total HH LDT (50/100) days/year shown on the secondary Y axis. N=72 HHs.

Referring to **Figure 76**, in 2 car ICE-BEV HHs, we notice a clear trend in decreasing ICE usage for LDT with an increase in the range of the BEV, and this effect is more pronounced in the case of LDT100. There was only a 6% reduction in ICE usage for LDT50 in Bolt-60 HHs (33%) compared to Leaf-30 HHs (39%). However, the reduction in ICE usage for LDT100 was greater in Tesla Model S HHs compared to Leaf HHs. Overall, on an absolute days/year basis, Leaf-24 HHs had the least number of LDT50 and LDT100 days compared to all other BEVs.

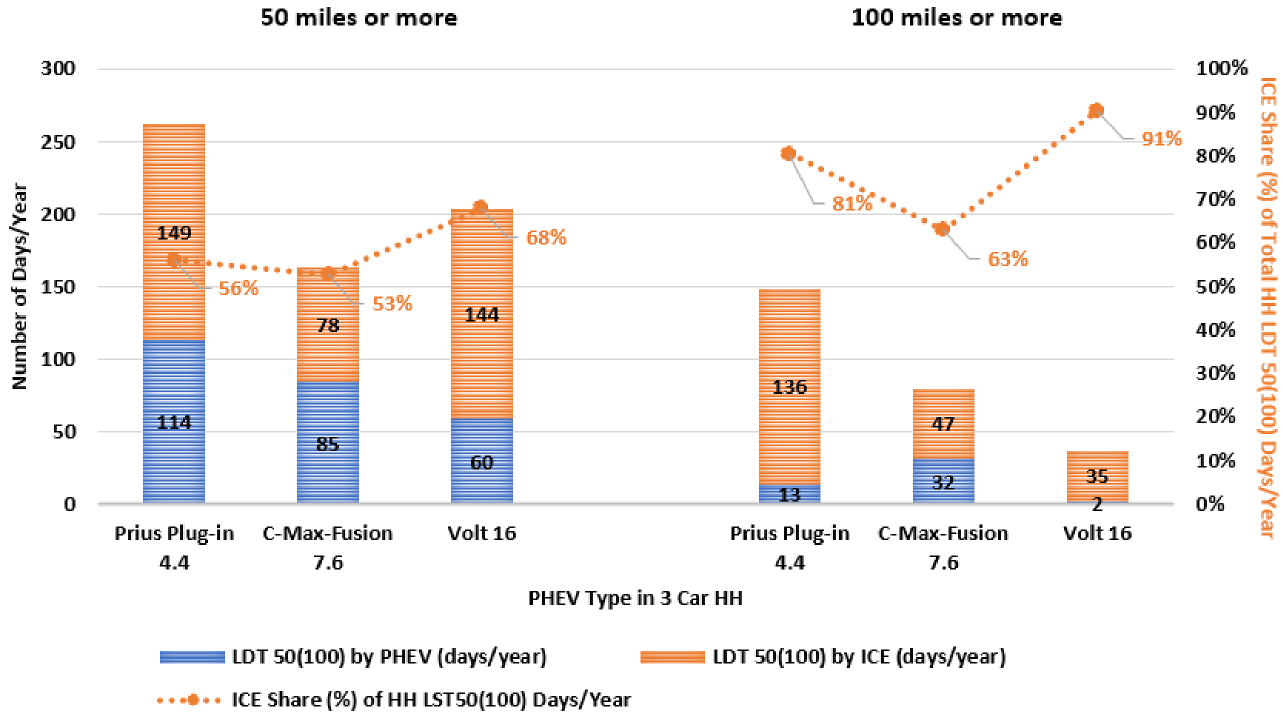


Figure 77. PHEV and ICE Use (Days/Year) for Long Distance Travel 50(100) Miles or More in 3 Car HHs (Two ICEs and Single PHEV); ICE Share (%) of Total HH LDT50(100) days/year shown on the secondary Y axis. N=12 HHs.

Figure 77 and **Figure 78** depict the average annualized number of days/year the PEV and ICE was used for LDT50 and LDT100 in 3 car PHEV and BEV HHs, respectively. The ICE share (%) of total HH LDT50/100 days is shown using the secondary Y axis in **Figure 77** and **Figure 78.**

Referring to **Figure 77,** in 3 car HHs**,** we can observe that the ICEs in Volt-16 HHs were used the most for LDT50 and LDT100 followed by the ICEs in Prius Plug-in-4.4 HHs and the ICEs in C-Max/Fusion-7.6 HHs.

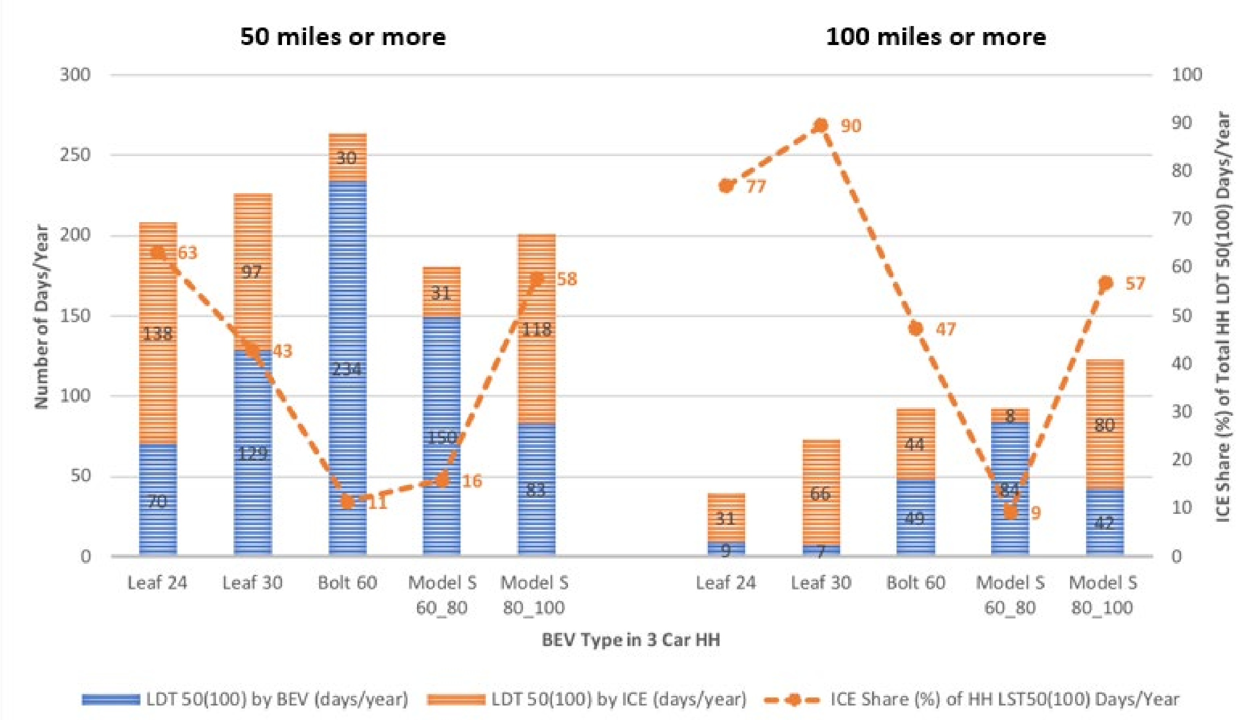


Figure 78. BEV and ICE Use (Days/Year) for Long Distance Travel 50(100) Miles or More in 3 Car HHs (Two ICEs and Single BEV); ICE Share (%) of Total HH LDT50(100) days/year shown on the secondary Y axis. N=12 HHs.

Referring to **Figure 78,** in 3 car HHs**,** we can observe that the ICEs in Leaf-24 HHs were used the most for LDT50, whereas the ICEs in Leaf-30 HHs were used the most for LDT100. The ICE usage in Bolt-60 and Tesla Model S-60_80 HHs for LDT50 was almost similar whereas the LDT 100 data showed no similarities in ICE shares across BEV types.

5 PHEV Engine Starts Analysis

5.1 Cold Starts

According to CARB's vehicle emission inventory model (EMFAC), for typical ICE vehicles, a cold start is defined as an engine ignition event after the engine has been off and the vehicle is stationary for 12 hours(CARB 2018). PHEVs have both a battery and an ICE engine and under certain circumstances, the ICE engine may go through an ignition event while the vehicle is already on the road after it was initially started by the battery. Under this circumstance the ICE engine in a PHEV may be going through both a cold start under the usual ICE vehicle definition while also being high power because it is already on the road and operating at an elevated speed or at high torque. In some PHEVs, the first time an engine starts may be when higher power is required at some point during a trip, negating some of the environmental benefits of reducing total number of cold engines starts results from completing trips and travel days on electric mode only and the benefit of the low total gas consumption. High-power engine starts have been associated with high local emissions of NOx and organic gases. Estimates based on dynamometer measurements demonstrate that during such events, blended PHEVs emit at rates higher than they do during the lower power start events that occur during emission certification tests(CARB 2017, Pham and Jeftic 2018).

The objectives of this section are to characterize the engine start activity profiles of PHEVs, including: 1) to define characteristics associated with all PHEV engine start events; 2) to identify conditions including driving behavior, battery level, and other factors that trigger high SOC start engine events; and 3) to determine the frequency of various types of starts. Further, more information is needed on total number of engine-starts and how these compare with conventional vehicles. The analysis of this activity data will be combined by CARB with previous emissions test results to better characterize real-world emissions levels and to improve a future version of CARB's EMFAC vehicle emission inventory model. Based on results of this project, regulators may want to work with car manufacturers to devise emission control strategies that mitigate high emission events during high power cold starts.

This study logged combined PHEV models (i.e., C Max/Fusion Energi) and non-blended PHEV models (i.e., Volt). The second-by-second logger activity data from the logged PHEV models were analyzed to better understand ICE-engine high power cold starts in the PHEVs described in this report. Because the data on some parameters was collected at high frequency (approximately once every 1 to 10 seconds), we can monitor the existing conditions in the few seconds before the engine starts in a PHEV. Our analysis was able to classify all engine starts by state of charge (SOC), soak time, travel distance, and speed. However, due to technical limitations inherit in the loggers in the second-by-second activity logging, we were unable to pinpoint the reason for engine starts, such as high-power requirement resulting from acceleration or a change in road grade.

The data collection was not synchronized for all parameters despite some parameters updating every 1 to 10 seconds. Furthermore, any parameter update generates a new timestamp and update of all the old values of the other parameters that were not updated. We cannot distinguish between parameters that have been updated but remained constant over several seconds versus those that have not been updated and are simply duplicated from the previous measurement. A quick split-second change in pedal position from 0% to 100% and back to 0%, for example, can be missed all together or alternatively "stuck" for a few seconds on 100%. To overcome this limitation, we used the maximum value recorded five and ten seconds before the engine start (RPM>500) to explore reasons for engine starts. For vehicle models older than 2019, the SOC On-Board Diagnostic (OBD) Parameter Identification (PID) value is not reported in a standardized way. Note that results for SOC reported here are shown as reported by the CAN bus, but may not reflect absolute battery SOC. Our logger reported modeled catalyst temperature only for the Volt and Energi. The data shows that cold starts happened mostly for the first engine start of a trip and even for the longer-range Volt we did not record even one cold start that is not the first in the trip. Our analysis, therefore, is focused on the first engine start in each trip.

5.2 Proportion of Days with Engine Starts

For PHEVs, engine starts are a function of many parameters, including SOC and power requirement, among others. **Figure 79** suggests a high correlation between battery size and days with no engine starts that is similar to the zero emission trips and zero emission miles described in Section 3.5. For example, the percentage of travel days that end without engine starts is around 4% for the short-range Prius Plug-in-4.4 compared to 17% for the Energi. The Volts have a relatively high percentage of zero-emission driving days (35%, 39%) because they are a non-blended PHEV. These percentages may be lower when including PHEV users who drive their vehicle primarily as a conventional non-plug-in hybrid (charge less than 4 times per month).

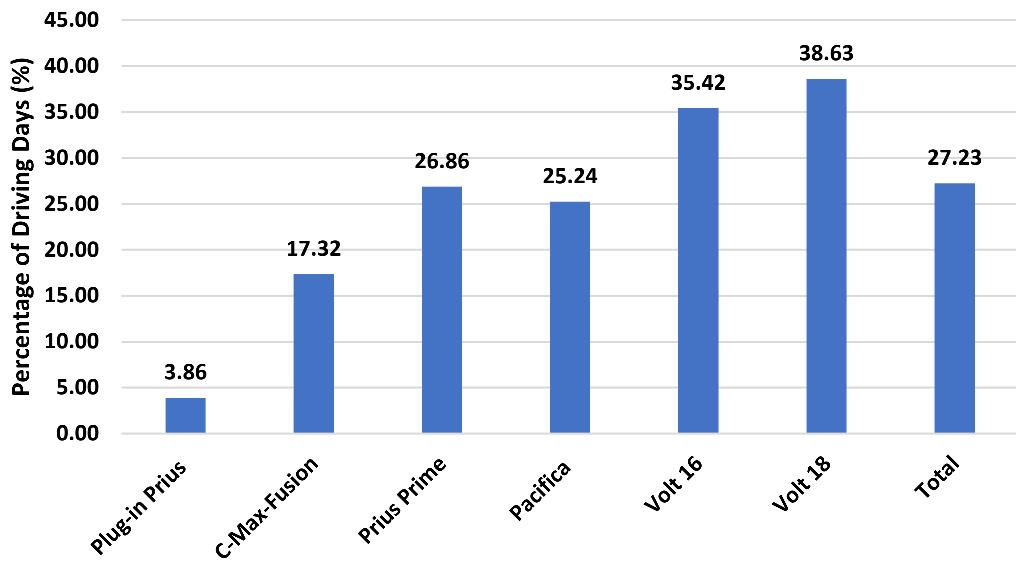


Figure 79. Share of Drive Days with No Engine Starts

5.3 Engine Start Event Description

The data collected per trip was chronologically ordered in a time series database to extract valid engine start events. An engine start event captures key metrics such as travel time and SOC within or around a timeframe in a trip wherein the RPM is greater than zero for more than 10 seconds. **Figure 80** provides a snapshot of the raw, time trace of a valid engine-on event. The total number of engine start events shared with CARB and used for this anlysis is 2,252,785 events, generated using data collected from 166 PHEVs, for up to one year per vehicle.

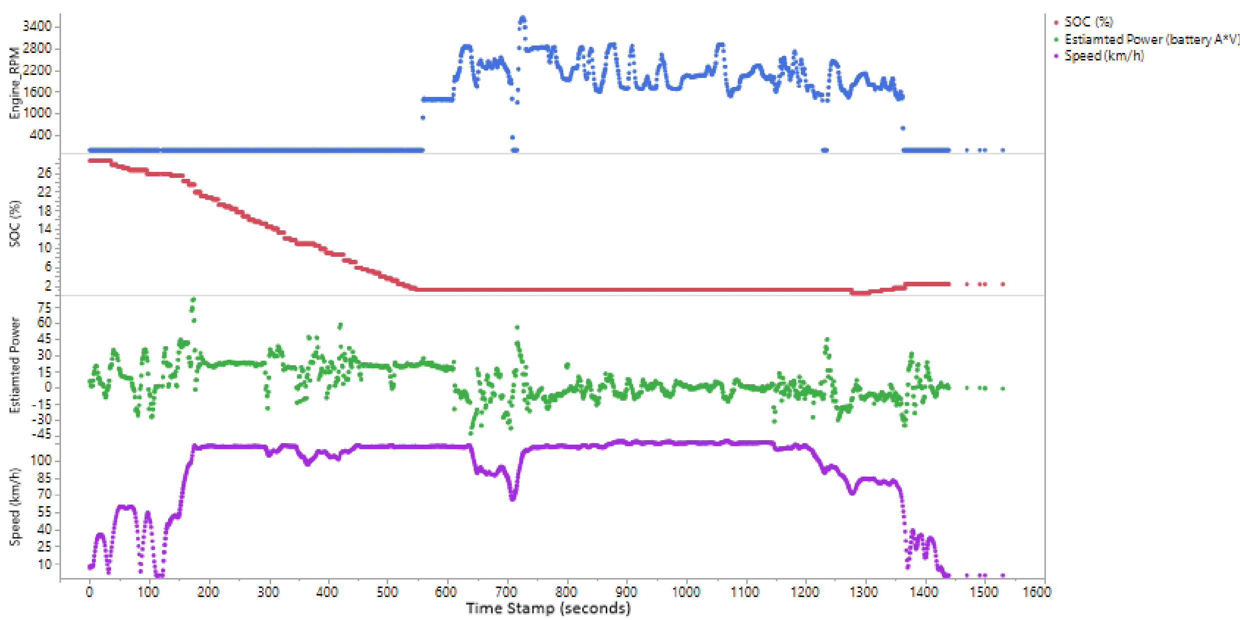


Figure 80. Engine-on Time Trace

It is critical to note that the sample frequencies of the collected data attributes are not always consistent. For instance, some attributes are collected every few seconds while other parameters are recorded only when a change in value is detected; in such cases, a distinction cannot be made between parameters that have been updated but remained constant over several seconds versus those that have not been updated and are simply duplicated from the previous measurement. This lack of synchronicity makes is extremely challenging to analyze the relationship between certain attributes. In **Figure 80,** for example, we have a consistent speed trace for 10 seconds with one change in pedal position 3 seconds in. We do not know if the speed change and pedal position change happened within 3 seconds as both events could have happened within 5-10 seconds from reporting.

5.4 Travel Conditions at Engine Start

We first isolated and analyzed the following metrics, recorded at or prior to engine start events: SOC, maximum power requirement (calculated based on battery current and voltage), and catalytic converter temperature when available. We then analyzed the engine soak time (i.e., time elapsed between two consecutive engine start events). Although we aimed to explore the relationship of vehicle power requirements with road grade, we could not do so due to the differing data sample rates and imprecise data values. The relationship with accelerator pedal position is based on max pedal position recorded 10 seconds before the engine start to cover for the data limitations.

5.4.1 SOC at Engine Start

One of the major causes for engine starts is the inability of the electric motor to propel the vehicle due to a low battery SOC (state of charge). We, therefore, explored the distribution of battery SOC when the engine is first turned-on within trips for all three PHEV models in the study. **Figure 81** illustrates this SOC distribution and highlights the fact that, for all vehicle models, most engine starts are invoked at a near-zero usable SOC (reported by the vehicle) as expected. Over 70% of Energi, Prius Prime-8.8 and Volt engine starts occur at SOCs below 5% while over 60% of Prius Plug-in-4.4 and Pacifica-16 engine starts occur at SOCs under 5%. As presented in previous sections, the Prius Plug-in-4.4 engine is more likely than the other models to start at high SOCs due to its relatively low battery capacity while the Volt engine is least likely to start at high SOCs due to being a non-blended PHEV and having a significantly higher battery capacity. The Pacifica-16's engine is more likely to start than other vehicles with similar battery capacities because it is a minivan, and therefore a heavier vehicle, leading to potentially higher overall power demand.

PHEV engine starts can be invoked by either low battery energy or high power demand. A PHEV can start its engine even with relatively high SOC if the power demand imposed on it exceeds the power that can be supplied by just its electric motor. Therefore, to decouple the effect of vehicle SOC and power demand, we developed three SOC classifications for engine starts. For all vehicle models, low or Empty (E) SOC is between 0% to 1%, medium (M) SOC is between 1% to 10%, and High (H) SOC is over 10%.

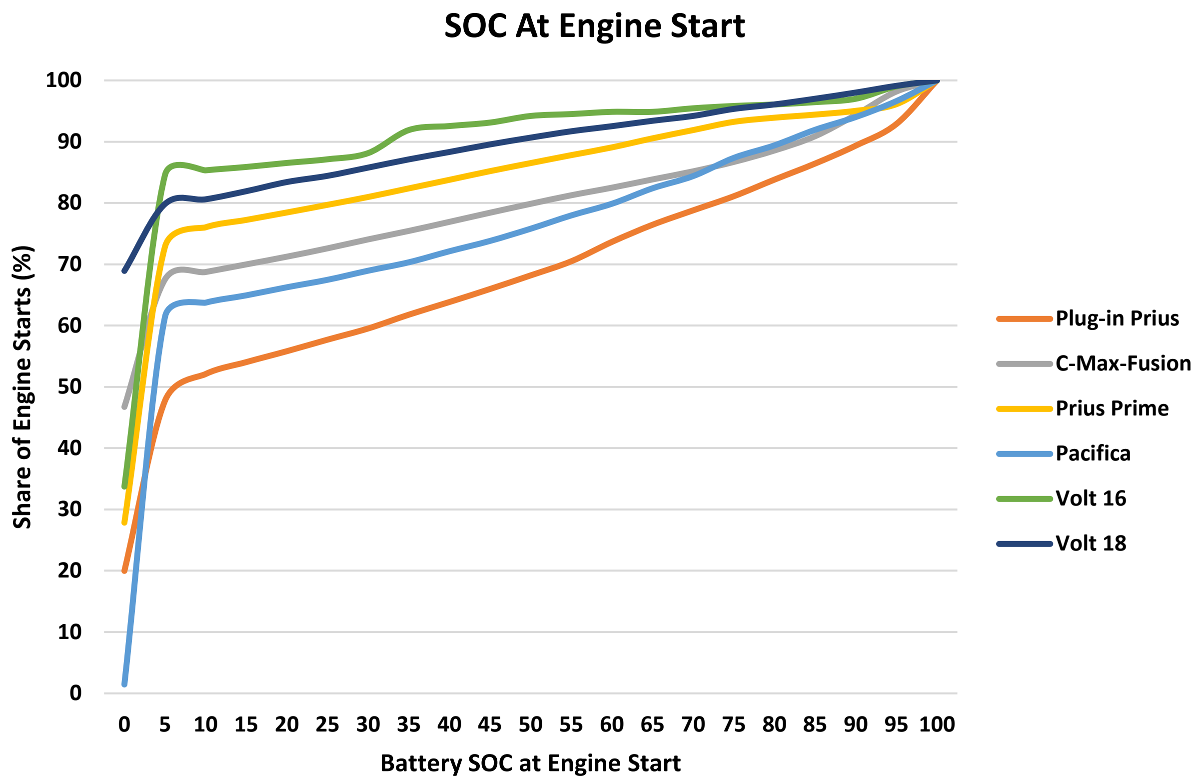


Figure 81. SOC at First Engine Start

5.4.2 Maximum Estimated Power Requirement before Engine Start

As discussed earlier, in certain driving situations such as traveling at high speeds or climbing a steep incline, a PHEV's power requirement may exceed the power that can effectively be provided by its electric motor, regardless of the vehicle's battery SOC; these situations can force the internal combustion engine to start up to provide the additional power required to propel the vehicle at an appropriate speed. We explored the distribution of the maximum power requirement 5 seconds before the first engine start within trips, acknowledging the potential error due to time reporting gaps between the parameters, broken down by the SOC classifications determined in section 5.4.1, for each vehicle model (**Figure 82**). For the PHEVs with relatively lower battery capacities such as the Prius Plug-in-4.4 and the Energi vehicles, most low SOC engine starts correlate with lower power requirements (0-12 kW) while majority of high SOC engine starts correlate with relatively higher power requirements (25-42 kW). On the other hand, the engine starts of PHEVs with relatively high battery capacities, such as the Volts, do not seem to correlate strongly with power requirements; these vehicles are least likely of the models to invoke an engine start in the incidence of high-power requirements, regardless of their SOC. However, the Pacificas, despite having battery capacities close to that of the Volts, seem to invoke the engine at medium and high SOCs under a wide range of power requirements. This is probably because the Pacificas, being classified as mini-vans, are much larger and heavier than the Volts, potentially leading to a higher incidence of greater power requirements from larger road loads. Overall, the Prius Plug-in-4.4 and Energi vehicles, having relatively smaller battery capacities, are more likely to turn on their engine to meet high power requirements while the Volts, being non-blended PHEVs and having a larger battery capacity, are least likely to start their engine in the presence of high-power requirements.

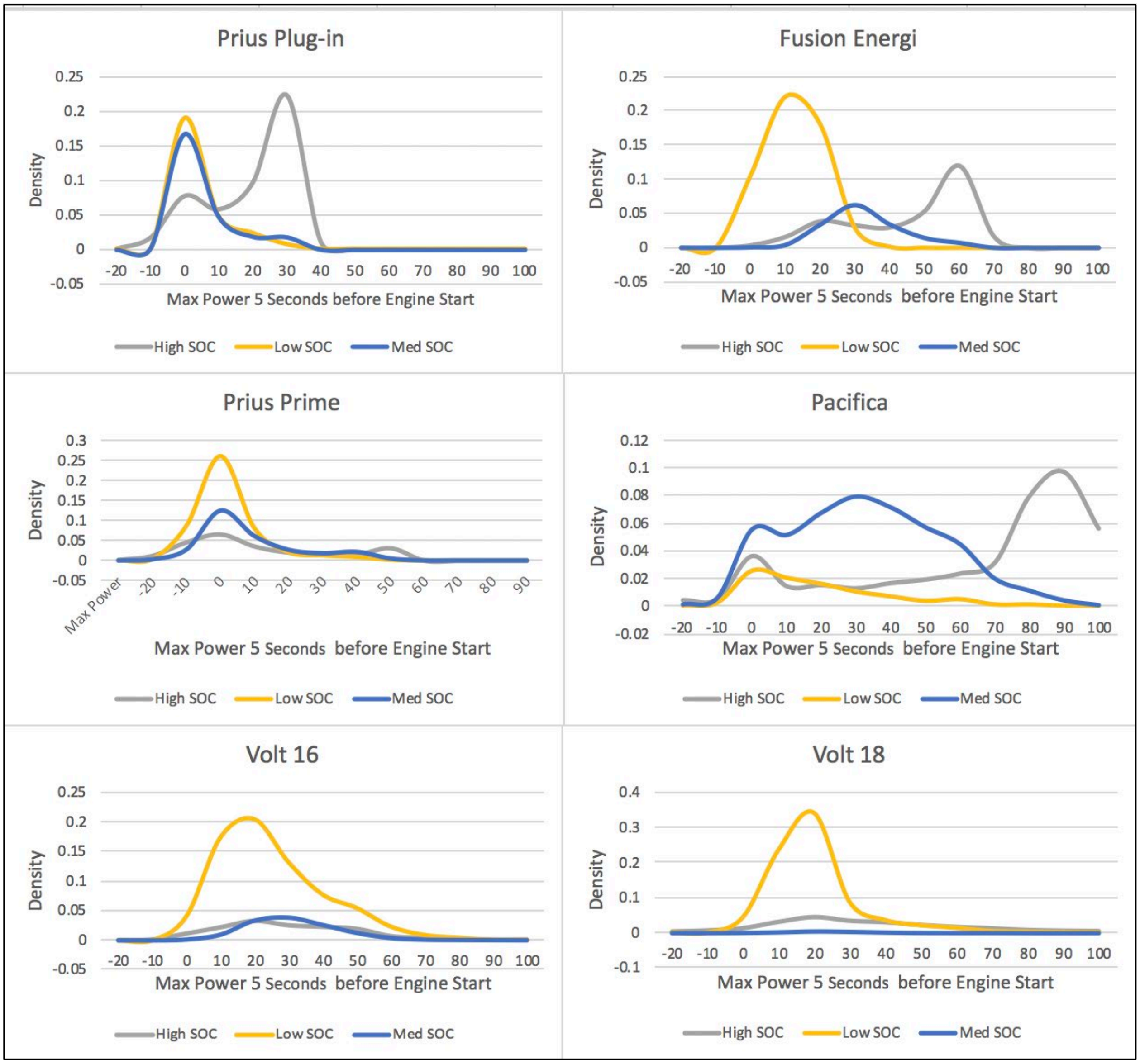


Figure 82. Maximum Power Requirement 5 Seconds before Engine Start

5.4.3 Catalyst Temperature before Engine Start

Our loggers captured modeled catalyst temperature data for only the Energi and Volt vehicles. For all engine start trips of these two PHEV models, we analyzed the distribution of catalyst temperature for the first engine starts and all subsequent engine starts separately, assuming that the first starts would include a mixture of cold and hot starts and that subsequent starts would include hot starts. **Figure 83** depicts the distribution of catalyst temperature of first engine starts in blue and all subsequent engine starts in red. For both vehicle models, around half of the first engine starts occurring at temperatures above ambient temperatures. We did not observe any cold starts after the first start for all trips even though 0.4% of the starts may not be fully warmed up to 425ºC. The lack of cold restarts could be because the vehicles are keeping the engine on for enough time to ensure that the first engine start warms the catalyst for any potential subsequent starts within the same trip. In addition, the time elapsed between consecutive engine starts is fairly small; among all the PHEV trips, the longest time elapsed between the first engine start and its successive start was 245 seconds (about 4 minutes) which is not enough time for the catalyst to completely cool off.

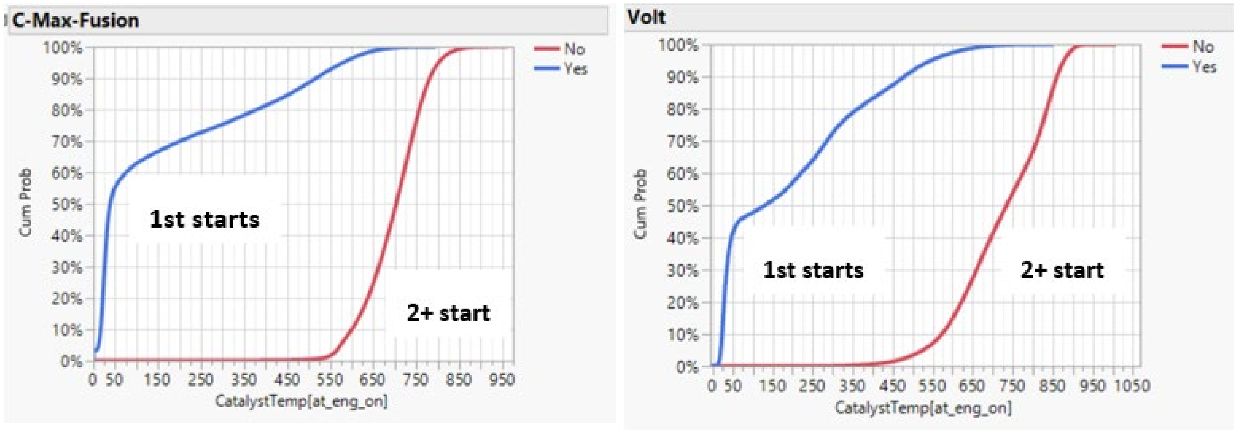


Figure 83. Catalyst Temperature at Engine Start

5.4.4 Engine Soak Time

For all engine start trips, we analyzed the time elapsed between two consecutive engine starts (soak time). This analysis includes any engine start regardless of travel distance and is based only on time and RPM. Engine starts that were not the first engine start of trips were filtered out; we solely studied the soak time of the first engine start of every trip. Cold starts were defined, as starts after 720 minutes (i.e., 12 hours) , which is consistent with EMFAC, with variation of warm starts depending on the minutes the engine is at idle. The soak time of each engine start was calculated by measuring the duration between it and the engine start preceding it. The SOC classification criteria derived in section 5.4.1 was again used to categorize the engine starts. **Figure 84** to **Figure 89** present the soak time distribution of Prius, Energi, Pacifica, and Volt engine starts, respectively.

For all vehicles, there seems to be an inverse relationship between soak times and engine start shares; the proportion of engine start events decay as soak time increases. For all PHEV starts, high SOC starts seems to be more prevalent with greater soak times. Engine starts with higher soak times may be more likely to have higher SOCs than engine starts with lower soak times because vehicle charging sessions are more likely to have occurred between trips that result in a high soak times given there is a relatively larger potential charging window.

For comparison to the PHEVs, **Figure 90** presents the soak time distribution of ICE vehicles starts from the conventional gasoline vehicles from the households participating in this study. The soak distribution from these conventional vehicles seems to be similar to that of the PHEVs.

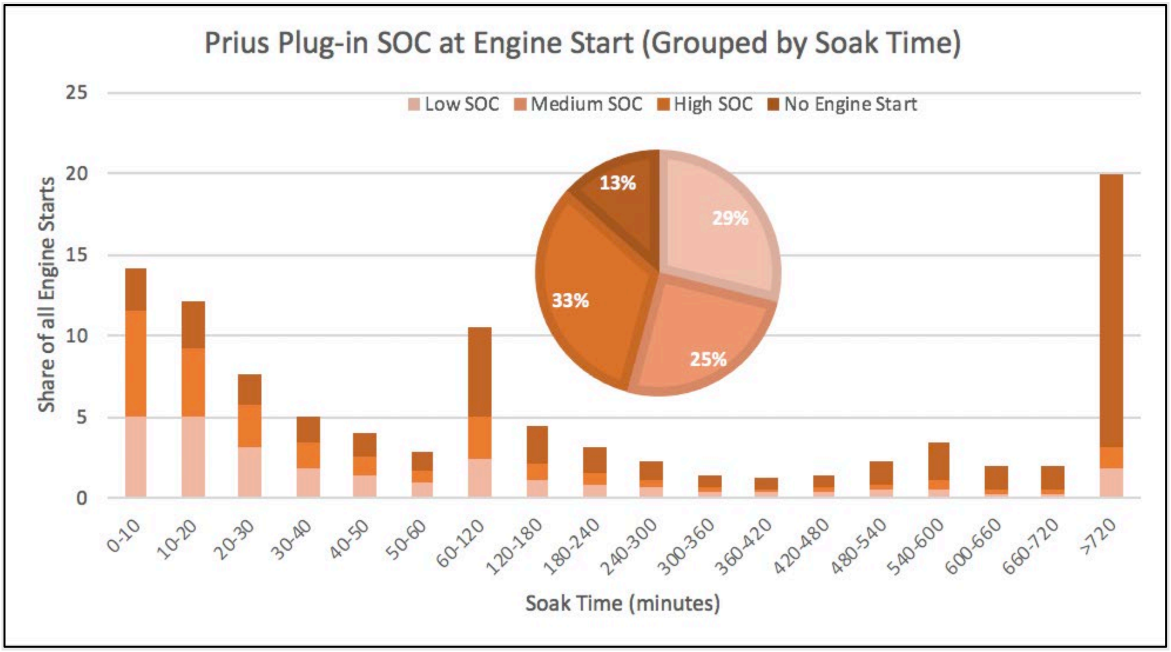


Figure 84. Prius Plug-in-4.4 Soak Time by SOC at Engine Start

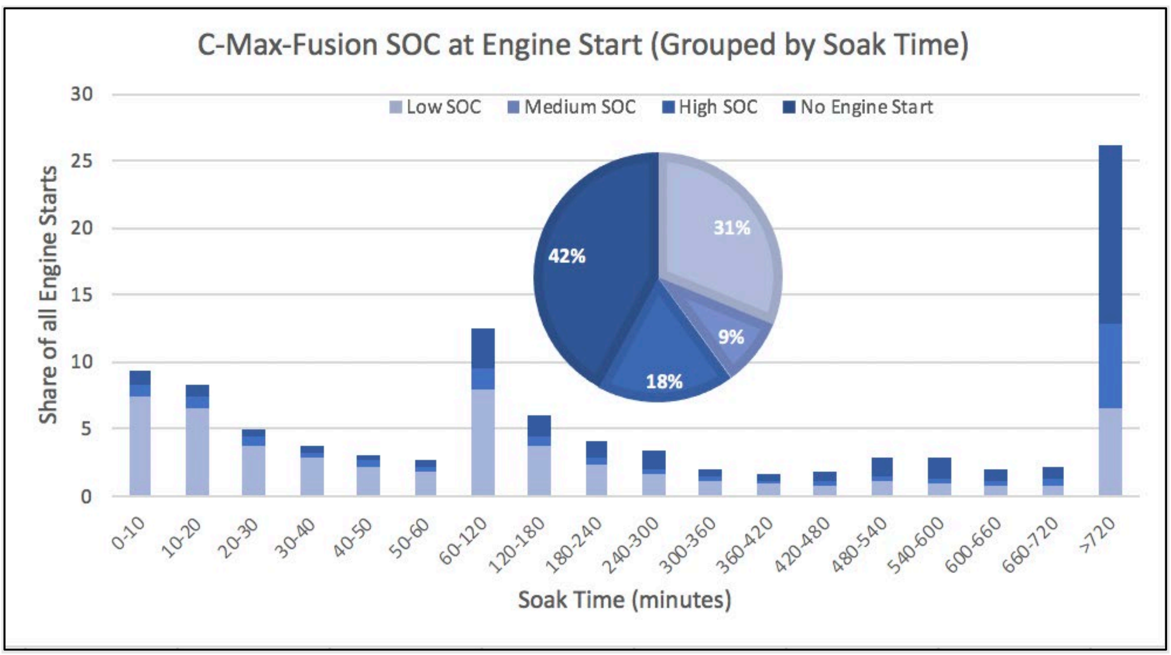


Figure 85. C-max Energi Soak Time by SOC at Engine Start

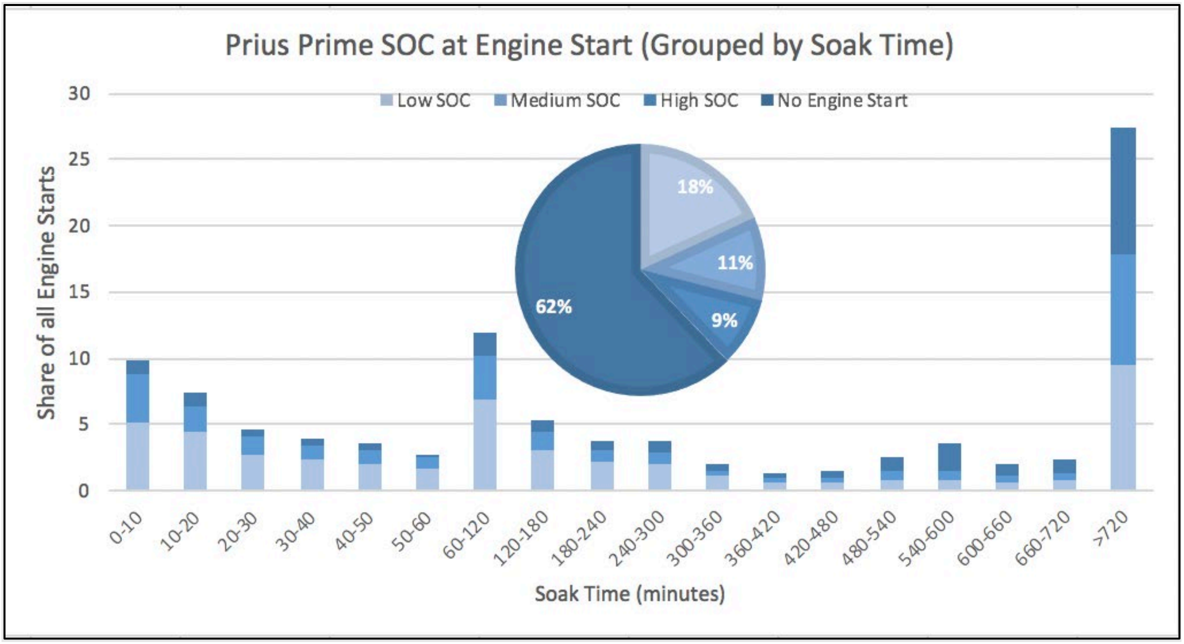


Figure 86. Prius Prime-8.8 Soak Time by SOC at Engine Start

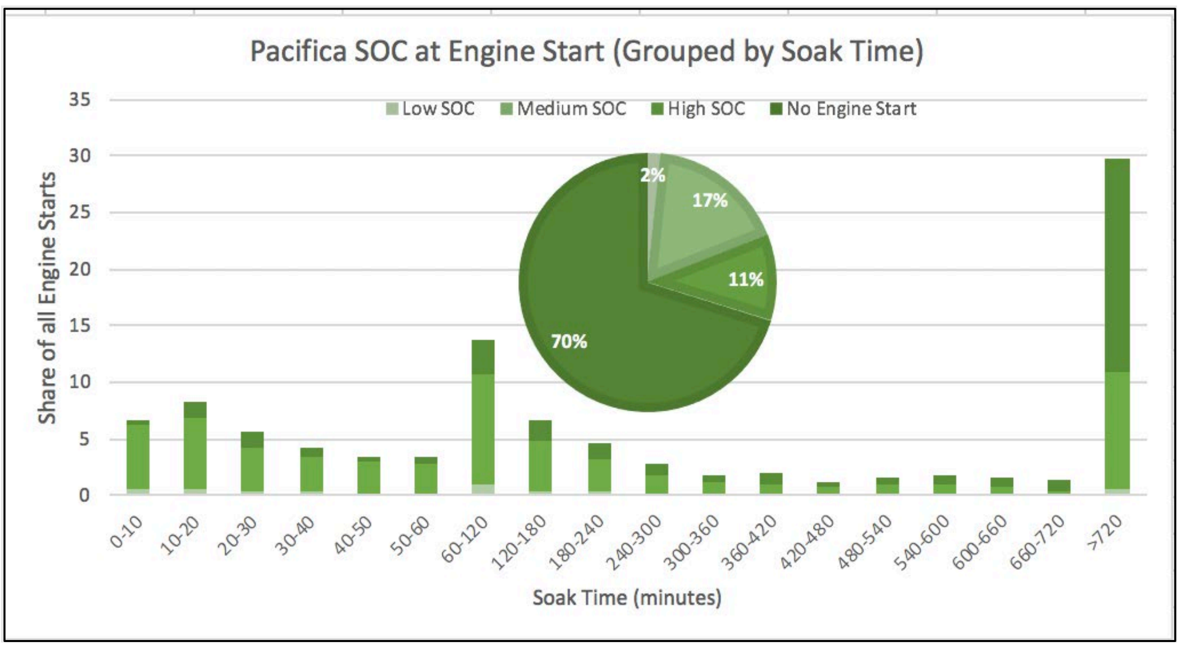


Figure 87. Pacifica-16 Soak Time by SOC at Engine Start

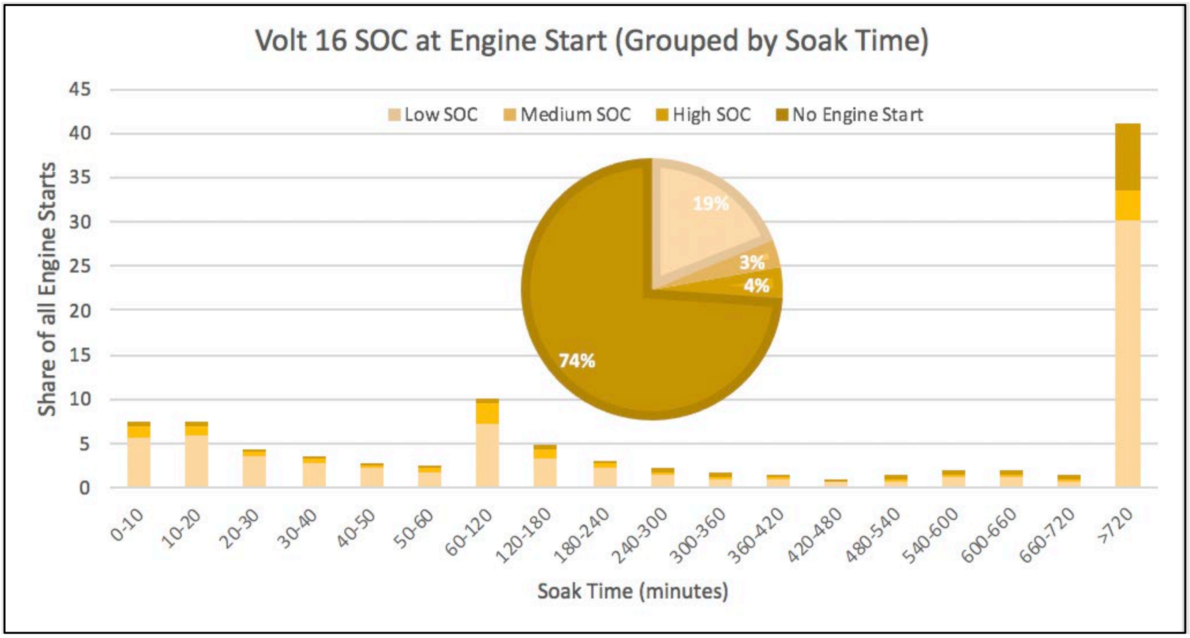


Figure 88. Volt-16 Soak Time by SOC at Engine Start

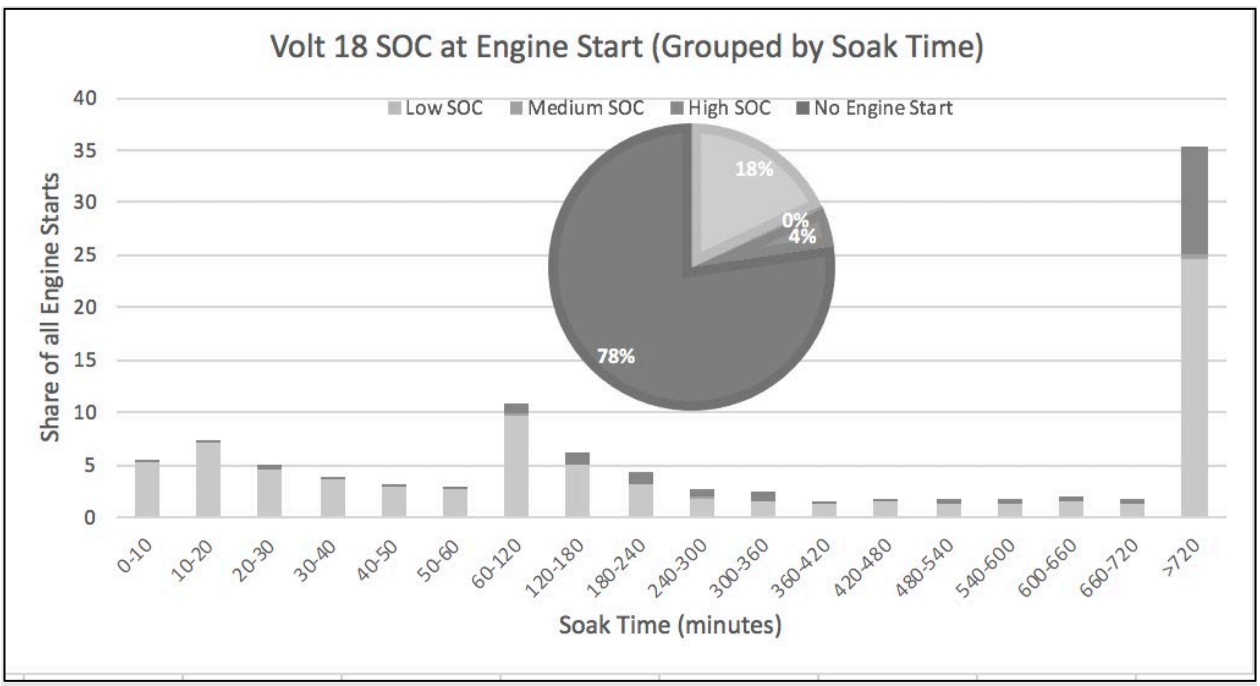


Figure 89. Volt-18 Soak Time by SOC at Engine Start

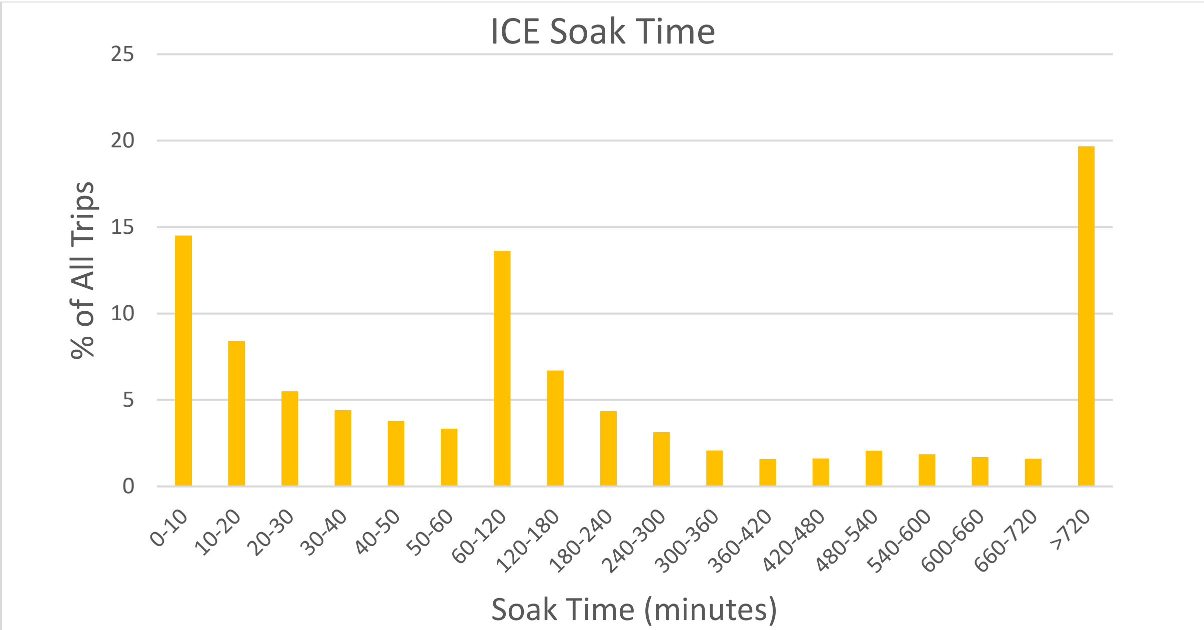


Figure 90. ICE Soak Time for the Conventional Gasoline Vehicles in Households

5.4.5 Distance Between Engine Starts

For each engine start trip, we analyzed two key distance metrics: the distance traveled from the beginning of a day to the first engine start of the day and the distance traveled from the beginning of a trip to the first engine start of the trip. To derive the first distance metric, we first grouped trips into days with a 3AM cutoff rather than the standard 12AM cutoff and then aggregated the distance of all trips that took place between the start of a day and the first engine start of the day for all days with an engine start. We chose a 3AM cutoff as it is the hour with the lowest trip frequency for all vehicle trips in our dataset. For the second distance metric, we simply calculated the distance from the start of a trip to the point at which the engine is first initiated for all engine start trips. For the first metric, we are only considering the first engine start of each day with an engine start while for the second metric, we are considering the first engine start of every trip. **Figure 91** and **Figure 92** depict the distribution of these two-distance metrics for all PHEV vehicles.

Over 80% of the Prius Plug-in-4.4’s first engine starts occurring after less than 5 miles of travel from the beginning of the day; most of these starts happening at medium to high SOCs. On the other hand, less than around 40% of the Prius Prime-8.8, Pacifica-16 and Volt first engine starts occur after less than 5 miles of travel from the beginning of the day; while in this case, most of the Volts’ starts occur at low SOCs, the Pacifica-16 starts occur at mostly medium to high SOCs. The Volts are also more likely to have engine starts after longer distances of travel from the start of the day than other PHEVs. The Energi vehicles have a lower proportion of engine starts than the Prius-Plug-in-4.4 and a greater proportion of engine starts than the Volts after less than 5 miles of travel from the beginning of the day. These observations are in line with section 5.4.2 which found that PHEVs with relatively small battery capacities such as the Prius Plug-in-4.4’s and the Energi vehicles are more susceptible to engine starts at medium and high SOCs than PHEVs with larger battery capacities such as the Volts, to meet high power demands. Overall, the occurrence of engine starts is more correlated to power demand than with SOC (vehicle range) for small battery PHEVs than it is for large battery PHEVs. For all PHEVs, over about 70%

of engine starts occurring after less than 5 miles of travel from the start of the trip; most of these starts happening at low to medium SOCs, suggesting that most engine start trips start with low SOCs.

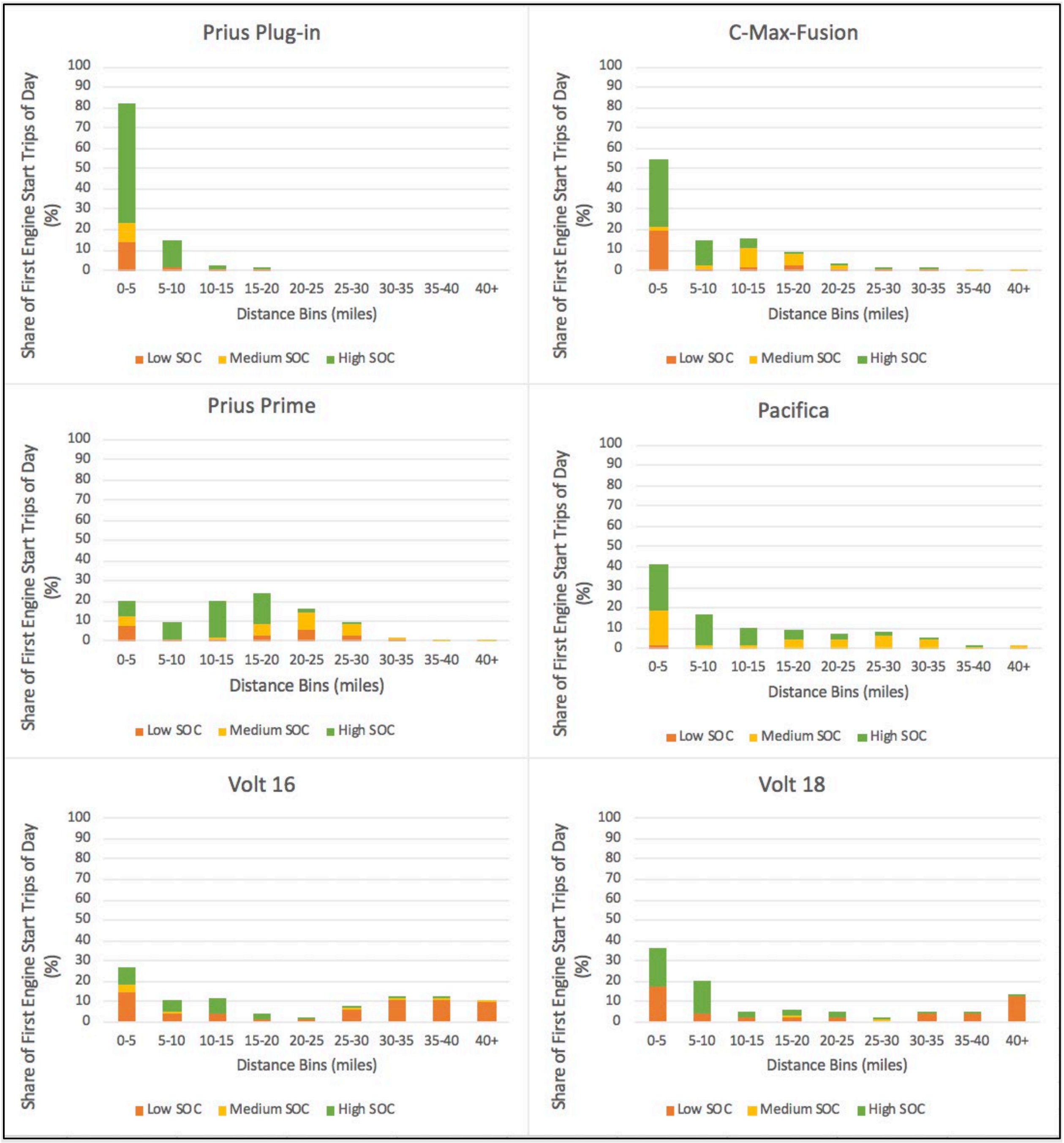


Figure 91. Distance from Start of Day to First Engine Start of Day for all PHEVs

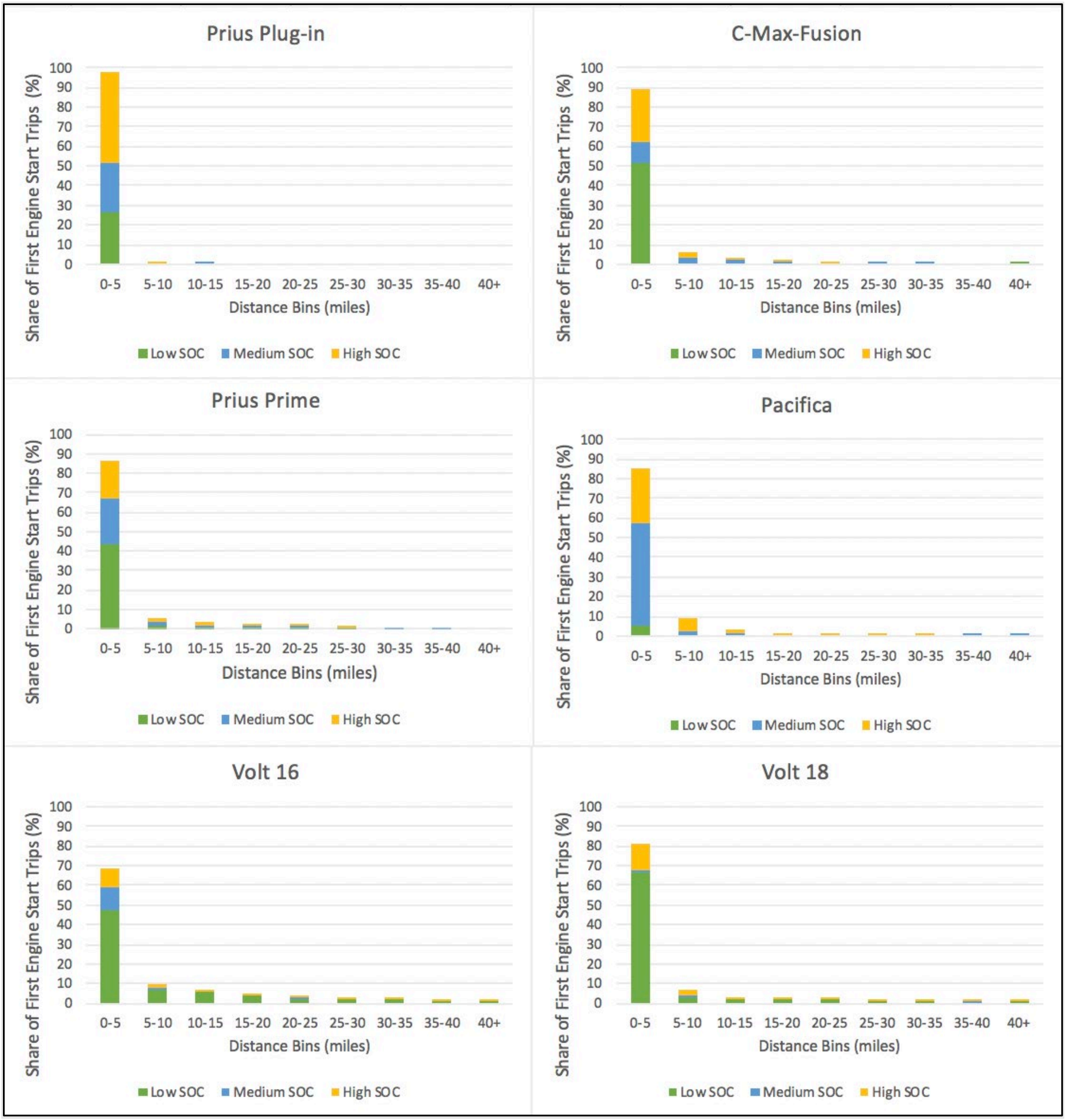


Figure 92. Distance from Start of Trip to First Engine Start of Trip for all PHEVs

5.5 Potential Emission Impacts of Engine Starts

Figure 93 illustrates the probability of various engine starts to occur on a given day for each vehicle model. The probabilities were derived from the annualized engine start days for each vehicle in the study. For this analysis, a cold start is an engine start with a soak time greater than 12 hours and a high-power cold start is a cold start with a maximum power requirement 5 seconds before the start of over 25 kW. There is an inverse correlation between vehicle battery capacity and the probability of an engine start with the Prius Plug-in vehicles having far more engine start days than the Volt vehicles. However, this is not the case for cold starts and high-power cold starts. The Prius Plug-in vehicles and the Volts logged fewer instances of cold starts than the mid battery capacity vehicles; this is probably because the Prius Plug-in starts it engine more frequently, resulting in shorter engine cool down periods than the other vehicles, while the Volt vehicles are least likely to start the engine in the first place given their larger battery capacity.

The mid-sized battery vehicles show large variation in engine start probabilities since, as observed in the previous section, there are several factors, ranging for low peak electric motor power to frequent high-power demands due to high curb weight, that determine when the engine is invoked for these cars. The C-Max-Fusion cars and the Pacificas, on average, have much higher proportions of cold start days than the other vehicles. The C-Max-Fusion cars have low electric motor power capabilities than the other vehicles, owing to its considerable proportion of high-power cold starts. The Pacificas, being minivans, are far heavier than the other models and so are more likely to have high power demand instances, resulting in a high frequency of cold starts despite their high battery capacity.

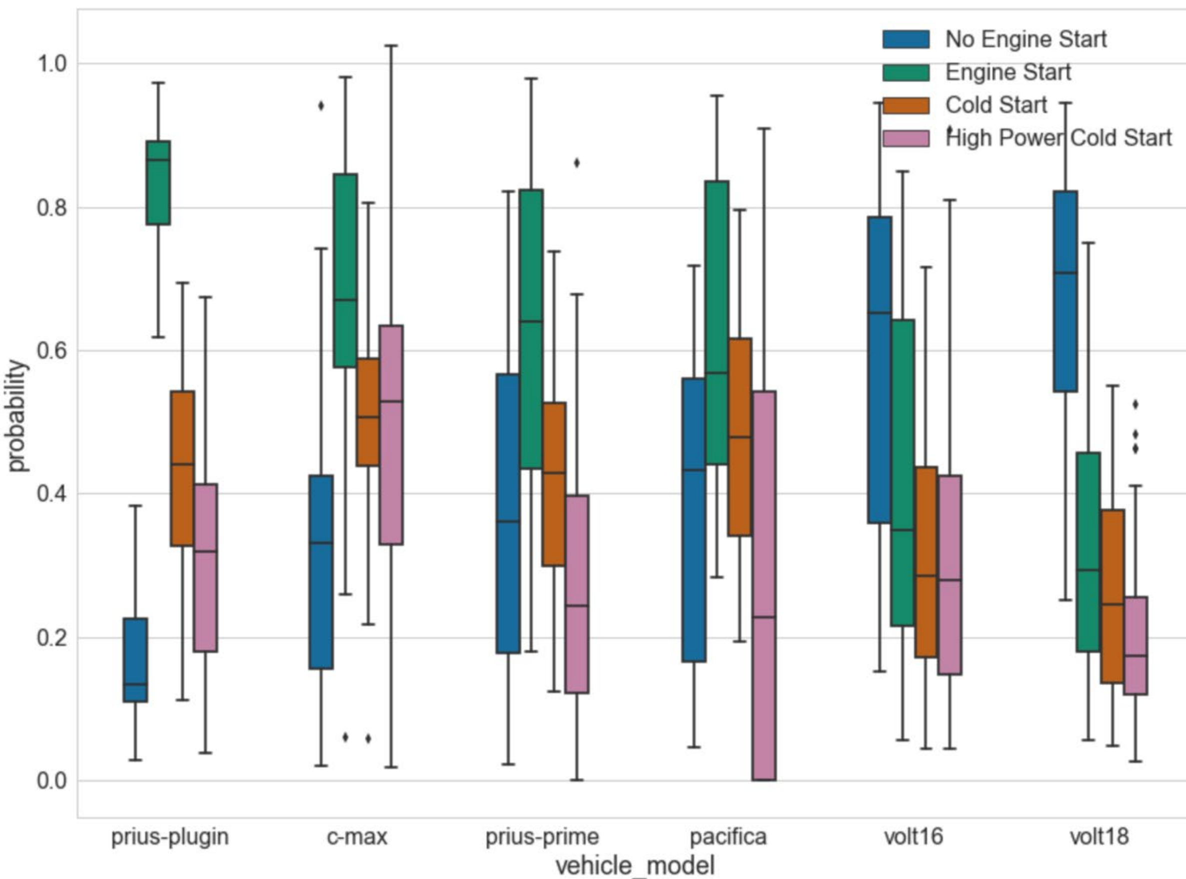


Figure 93. Probability of Engine Start per Vehicle Model (Derived from Annualized Engine Start Days)

Figure 93 depicts the average number of daily cold starts that occur for each vehicle model juxtaposed with the average number of daily cold starts if the models behaved like conventional ICE vehicles with the engine being invoked at the beginning of every trip. As expected, the Volts had fewer real cold starts than their hypothetical ICE cold starts given that their larger battery capacity and drivetrain design seek to reduce engine starts to optimize fuel displacement. The Plug-in Prius also had few real cold starts compared to its hypothetical ICE vehicle performance since it is more likely to have shorter engine cool down periods between starts than the other vehicles. The C-Max-Fusion vehicles and Pacificas do not seem to have a stark difference between actual cold starts and Hypothetical ICE cold starts because they are more likely to have high-power requirement instances during trips, owing to their low electric power capabilities or high curb weight. The mid capacity battery vehicles are less likely than the Prius-Plug in cars to have short engine cool down periods between starts and more likely than the Volts to have engine starts, making then more prone to cold starts than PHEVs with considerably lower or higher battery capacities. Overall, the Volts do a much better job than the other vehicles at both curbing start emissions via logging very few engine starts and maximizing fuel displacement.

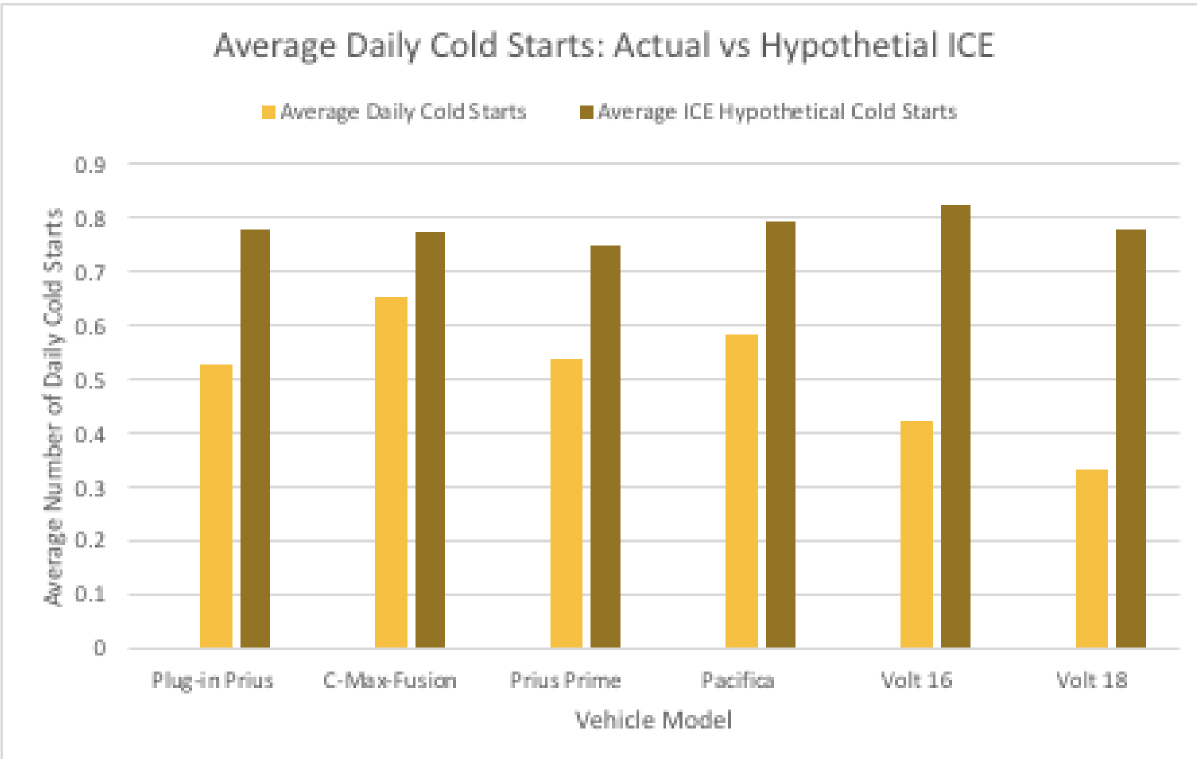


Figure 94. Average Daily Cold Starts

5.6 Engine Starts Discussion

This section includes only the initial analysis of the data collected. The main task of this project was to provide to CARB the full dataset of engine starts including the events before and after the engine starts for further analysis. The data preparation included quality control and cleaning missing and bad data results from problems in logger configurations. We also tested the GPS elevation data using GIS models and conclude that the accuracy level was not sufficient for energy and power analysis. Overall, the data collected, and the sample times are not sufficient for calculating their power requirement and other factors for engine starts. Nevertheless, data analysis shows that long-range plug-in hybrids can finish many days and trips without any engine starts. We also conclude that long-range plug-in hybrids engine starts are mostly correlated with battery state of charge, while short range PHEVs' engine starts may be correlated with other factors. For all vehicles, there seems to be an inverse relationship between soak times and engine start shares; the proportion of engine start events decay as soak time increases. For all PHEV Starts, high SOC starts to seem to be more prevalent with greater soak times; engine starts with higher soak times may be more likely to have higher SOCs than engine starts with lower soak times because the vehicles had more time to potentially recharge their batteries.

The probability of an engine start to occur in a day, for each model, can be explained by the models' individual specifications. In general, there is an inverse correlation between vehicle battery capacity and the probability of an engine start with the Prius Plug-in vehicles having logged far more engine start days than the Volt vehicles. However, this trend does not hold for cold starts and high-power cold starts. The Prius Plug-in vehicles and the Volts logged fewer instances of cold starts than the mid battery capacity vehicles; this is probably because the Prius Plug-in starts it engine more frequently, resulting in shorter engine cool down periods than the other vehicles, while the Volt vehicles are least likely to start the engine in the first place given their larger battery capacity. The mid-sized battery vehicles show large variation in engine start probabilities since there are several factors, ranging for low peak electric motor power to frequent high-power demands, that determine when the engine is invoked for these cars.

Comparing the average daily cold starts for each PHEV model to the average daily cold starts if the model vehicles behaved like conventional ICE vehicles showed that all models would have logged more cold starts if they behaved as ICE vehicles, suggesting that they all incur start emission savings functioning as PHEVs. The vehicles with mid electric range are less likely than those with low electric range (Prius Plug-in) to have short engine cool down periods between starts and more likely than those with high electric range (Volt) to have engine starts, making them more prone to cold starts than PHEVs with lower or higher battery capacities. There was a 136% increase in cold starts for the Volt 18 vehicles if they behaved as ICE vehicles compared to just 11% increase in cold starts for the C-Max-Fusion cars. The Volts, the PHEVs with the highest electric range, do a much better job than the other vehicles at both curbing start emissions via logging very few engine starts and maximizing fuel displacement as suggested by their relatively high electric miles to total miles ratio.

6 Fuel Cell Vehicle Analysis

In this section, we present the data collected from Fuel Cell Vehicle (FCV) usage at the vehicle and household level using data collected from the loggers. In total, we have 12 Toyota Mirais in our FCV dataset, but one Mirai was dropped from our analysis as it had trouble acquiring key data points (speed, GPS, etc.) for lengthy periods of time within its logging window. The remaining 11 vehicles that have reliable data for calculating key distance, speed, and energy metrics for at least 120 days are included in the analysis. Problems with logger reliability allow us to use only 60% of the days when loggers were installed, loggers that were connected for more than one year.

FCVs have driving ranges of more than 300 miles and can be refueled in less than 10 min at a hydrogen fueling station. Three original equipment manufacturers (OEMs) currently offer FCVs in California, with the Toyota Mirai being the most common (**Figure 95**). Sales of these vehicles began in 2014, with most vehicles leased for a period of three years. In most cases, hydrogen fuel cost is subsidized by the OEM.

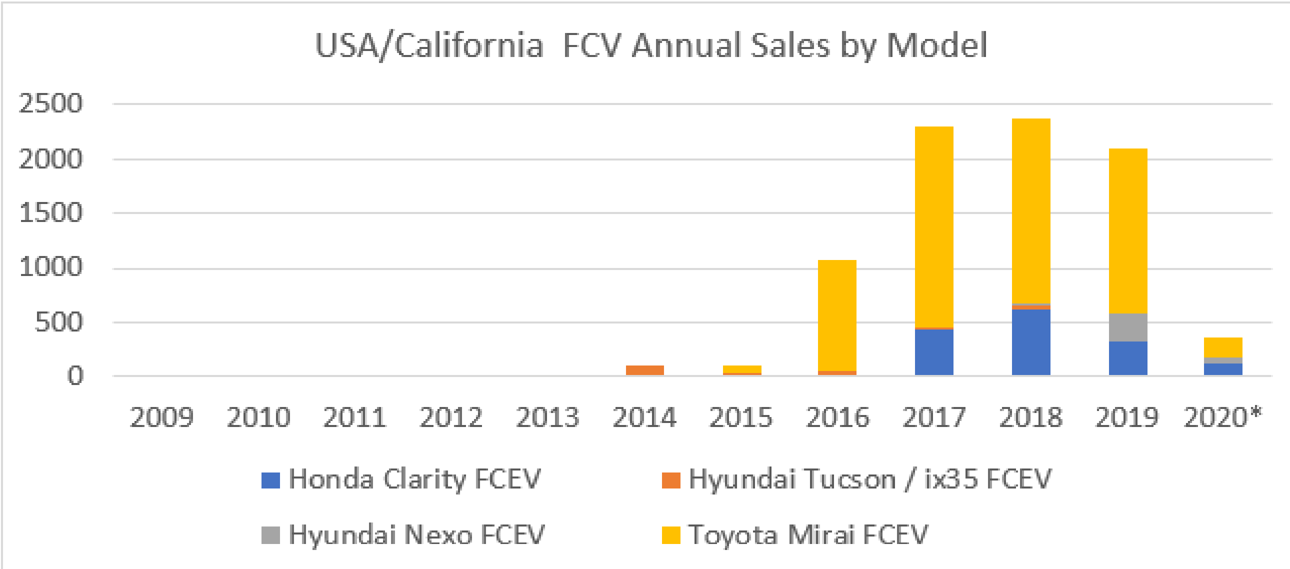


Figure 95. Fuel Cell Vehicle Sales by Model, Country, and Model for California

California currently has 41 active hydrogen-fueling stations, built through a combination of industry funds and capital and operating cost support from the California Energy Commission (CEC). These are in the Los Angeles, San Francisco Bay, and Sacramento areas as shown in **Figure 106**. In our study, we focus on the Toyota Mirai which can hold approximately five kilograms of compressed hydrogen gas, enabling it to travel up to 312 miles on a full tank. The descriptive summaries and analyses of the FCVs are presented in **Table 25-Table 26** and visualized in **Figure 96-Figure 97**. **Table 25-Table 26** summarize the data collected on FCV driving and refueling. As we did for filtering BEV and PHEV trips, we used a distance threshold of 1 km to filter out GPS noise and noticeably short trips recorded by the loggers with zero to minimal energy usage. Overall, around 88% of FCV VMT still remained after filtering. The refueling sessions were not directly reported by the loggers but were determined by looking at the difference between the fuel levels of consecutive trips; if there is a significant difference the ending fuel level of a trip and the starting fuel level of the trip immediately following it, we gauged that a refueling event occurred between those trips. Unfortunately, fuel level was one of the raw data points that was reported very sparsely by the loggers for most vehicles, so we probably failed to capture some refueling events that occurred within the logging window of each vehicle.

Table 25. FCV Driving Data Overview

FCV Type	Number of Vehicles	Raw Data Trips	Raw Data Total VMT	Filtered Data Trips	Filtered Data Total VMT	Filtered Data Average Driving Days/Vehicle
Mirai	11	15301	104133	11327	91164	247

Table 26. FCV Refueling Data Overview

FCV Type	Number of Vehicles	Refueling Sessions	Total Hydrogen (kg)	Total Refueling Days
Mirai	11	408	823.4	228

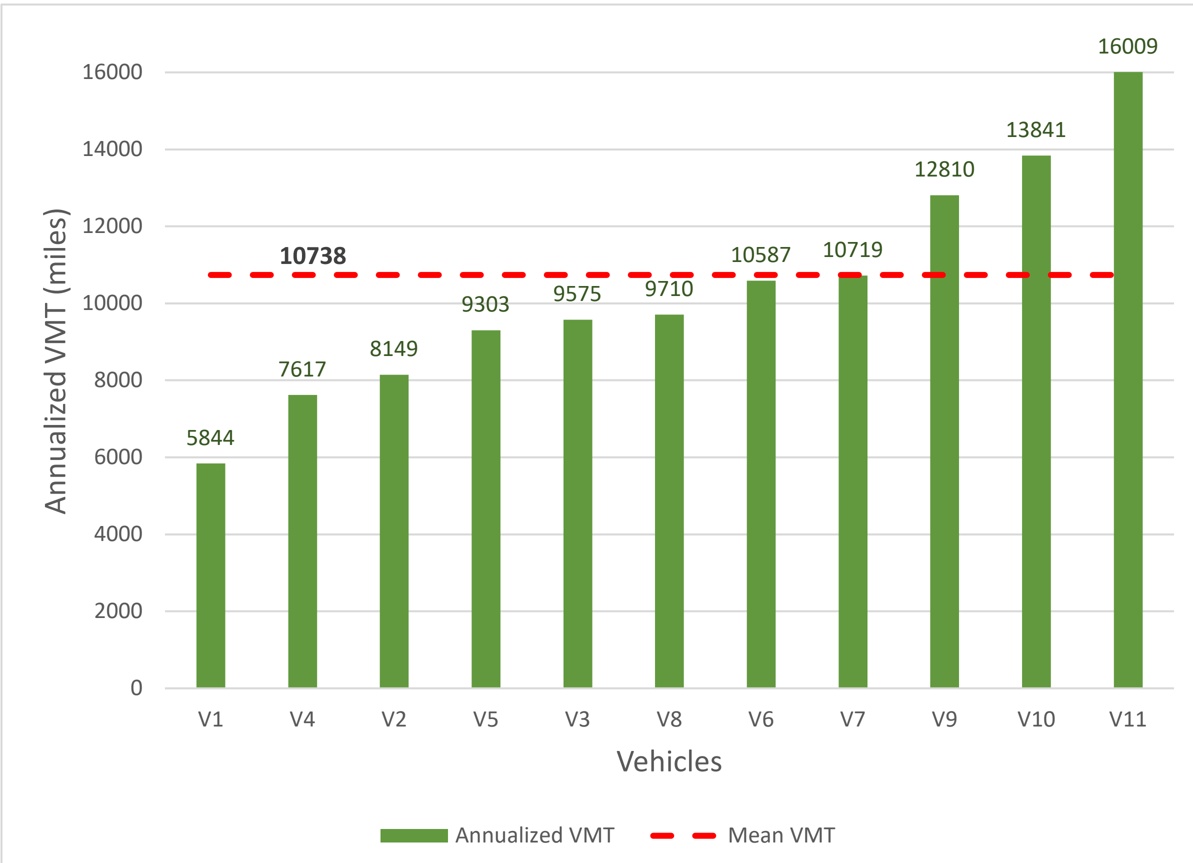


Figure 96. Annualized VMT of Mirais

Figure 96 shows the annualized VMT of the Mirais based on data collected from the loggers. The fleet average annualized VMT for the Mirais is 10,738 miles. There is a difference of over 10,000 miles between the vehicle with the highest annualized VMT and the vehicle with the lowest annualized VMT, showing a wide range in vehicle mileage.

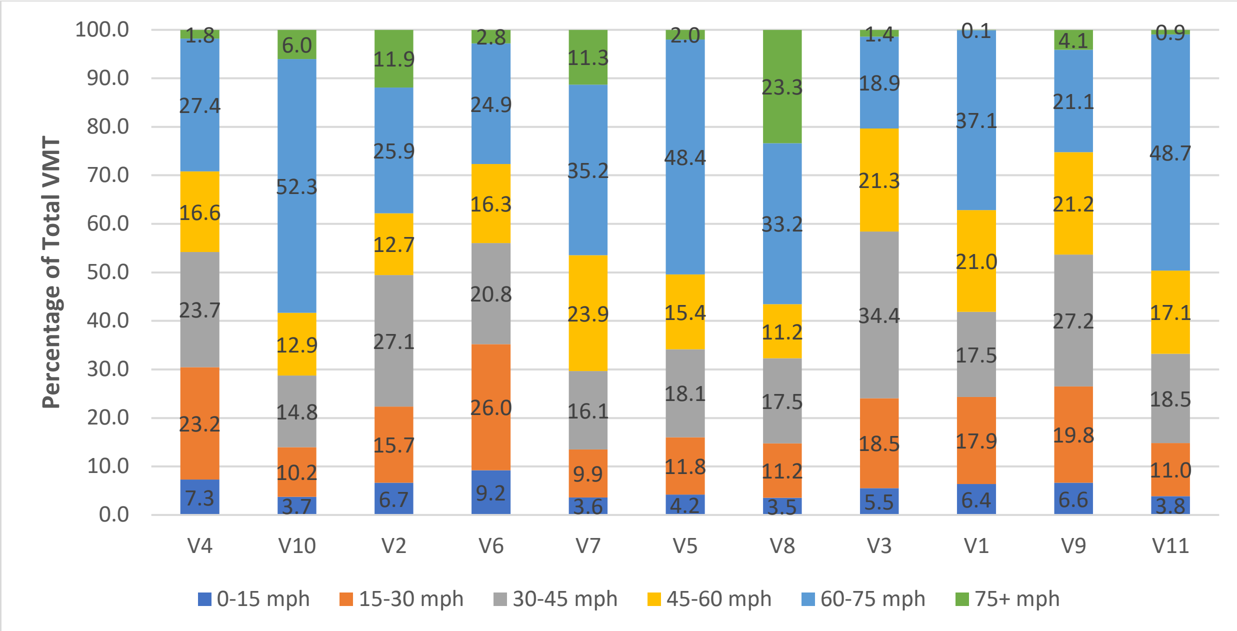


Figure 97. Mirai: Percentage Share of Total VMT by Trip Speed (in mph)

Figure 97 depicts the share of total VMT by trip speed bin for each Mirai. Most vehicles cover a high proportion of miles at speed of 30-75 mph and cover very few miles at speeds over 75 mph. V8, however, covers a considerable proportion of miles at speeds over 75 mph.

6.1 Fuel Cell Vehicle Driving

Table 27 and **Figure 98-Figure 102** provide descriptive summaries of Mirai driving patterns captured by data collected from the loggers. As shown in **Table 27**, on average, Mirai drivers, make around 4 trips per day with each trip ranging from 6 to 11 miles. There is extremely low variation in hydrogen usage amongst the vehicles; all vehicles consistently use about 0.02 kg of Hydrogen, on average, for covering one mile. The average trip distance of Mirai weekday trips is higher than the average weekend trip distance by about 2 miles while there is around a 23-mile difference between the maximum distance of weekday and weekend trips. 70% of the trips of half the vehicles (namely V1-V5) were less than 35 miles long whereas roughly 60% of the trips of most of the remaining vehicles (V7-V11) were over 35 miles.

Table 27. Mirai Driving Trip Level Summaries (on days when the FCV was driven)

Mirai Vehicles	Average Trips/Day	Average Trip Distance (miles)	Average kg(H2)/Trip	Average kg(H2)/Mile	Average VMT/Day (miles)
V4	4.11	7.29	0.12	0.0163	21.71
V10	5.86	8.14	0.16	0.0204	42.18
V2	3.76	6.69	0.12	0.0168	10.28
V6	4.75	6.93	0.14	0.0206	32.13

Mirai Vehicles	Average Trips/Day	Average Trip Distance (miles)	Average kg(H2)/Trip	Average kg(H2)/Mile	Average VMT/Day (miles)
V7	3.85	8.57	0.19	0.0266	38.53
V5	4.09	7.52	0.15	0.0208	26.48
V8	3.70	10.25	0.20	0.0191	36.2
V3	4.14	6.81	0.12	0.018	25.36
V1	4.18	5.59	0.09	0.0157	17.7
V9	4.00	10.54	0.20	0.0208	43.58
V11	4.96	11.00	0.18	0.0182	52.05
All Vehicles	4.13	8.05	0.15	0.019	30.8

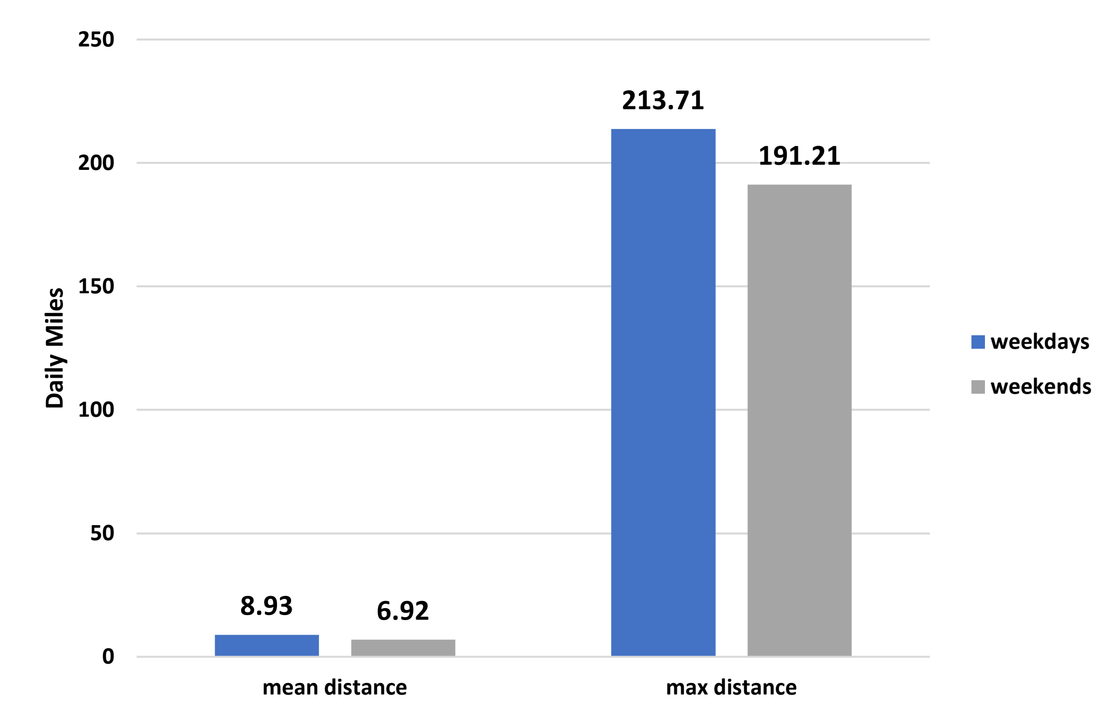


Figure 98. Average and Maximum Trip Distance on Weekdays and Weekends by Mirai

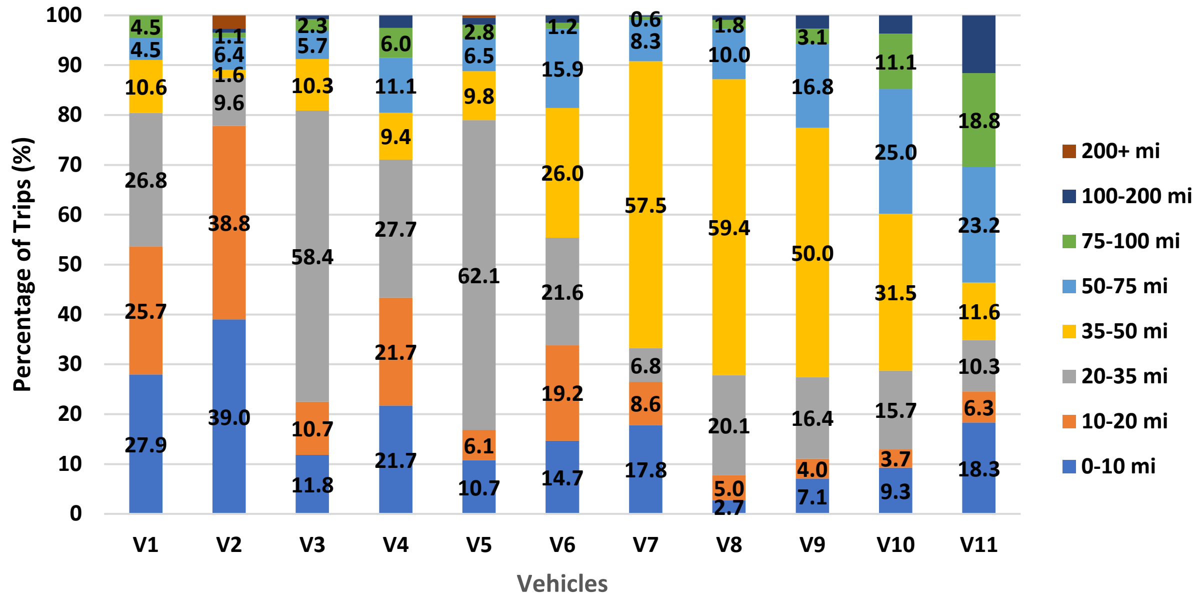


Figure 99. Percentage of Trips per Vehicle by Trip Distance Bins (miles)

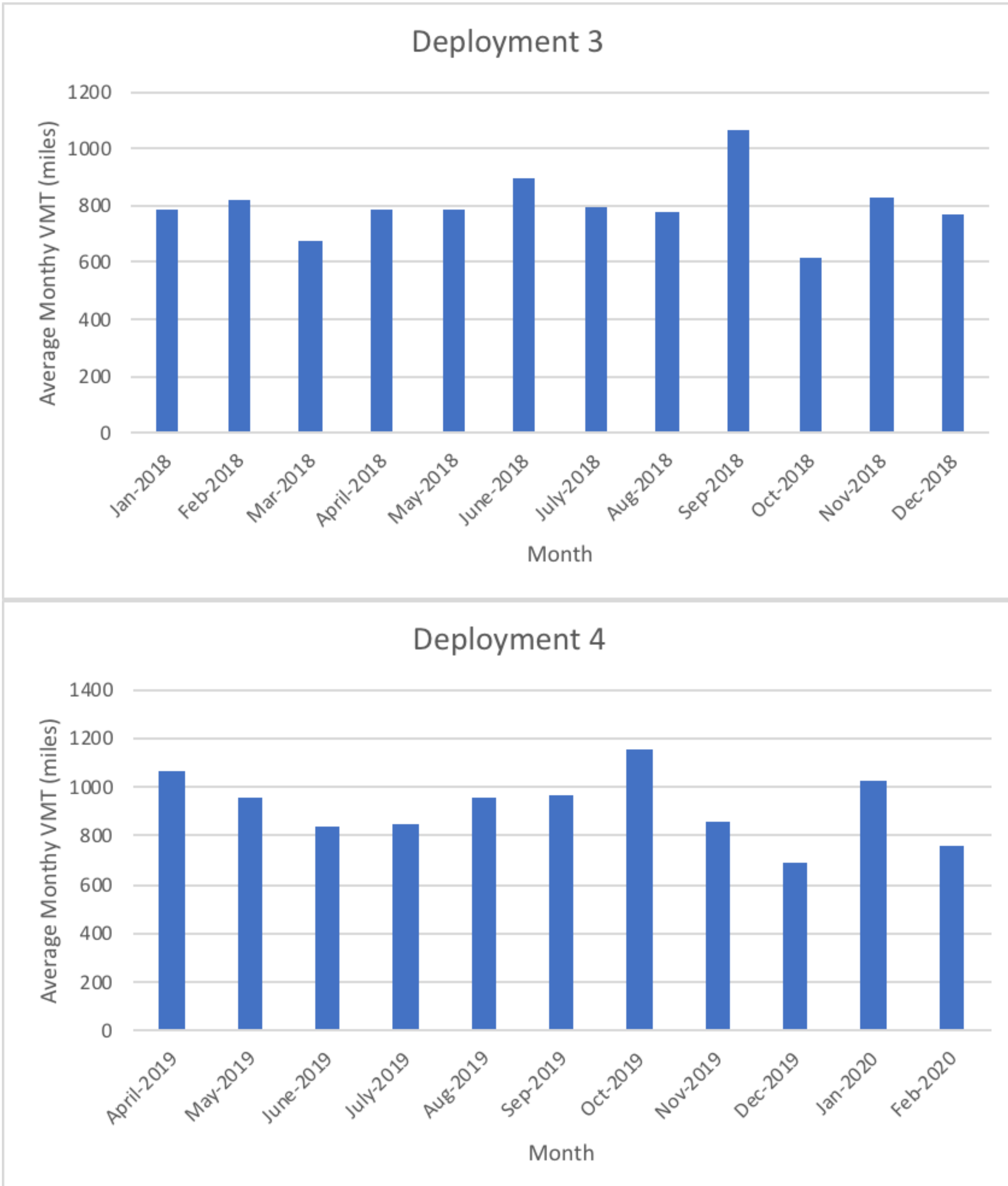


Figure 100. Average Monthly Vehicle VMT Across Deployments

Figure 100 depicts the monthly average VMT of the Mirais in the dataset broken down by individual deployments.

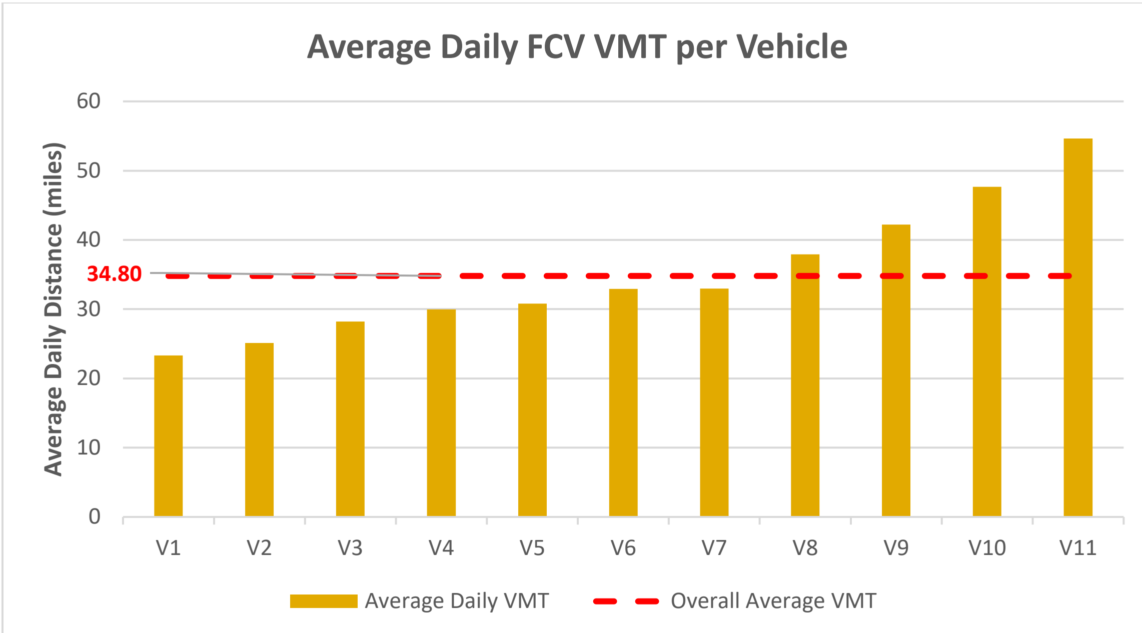


Figure 101. Average Daily FCV VMT per Vehicle

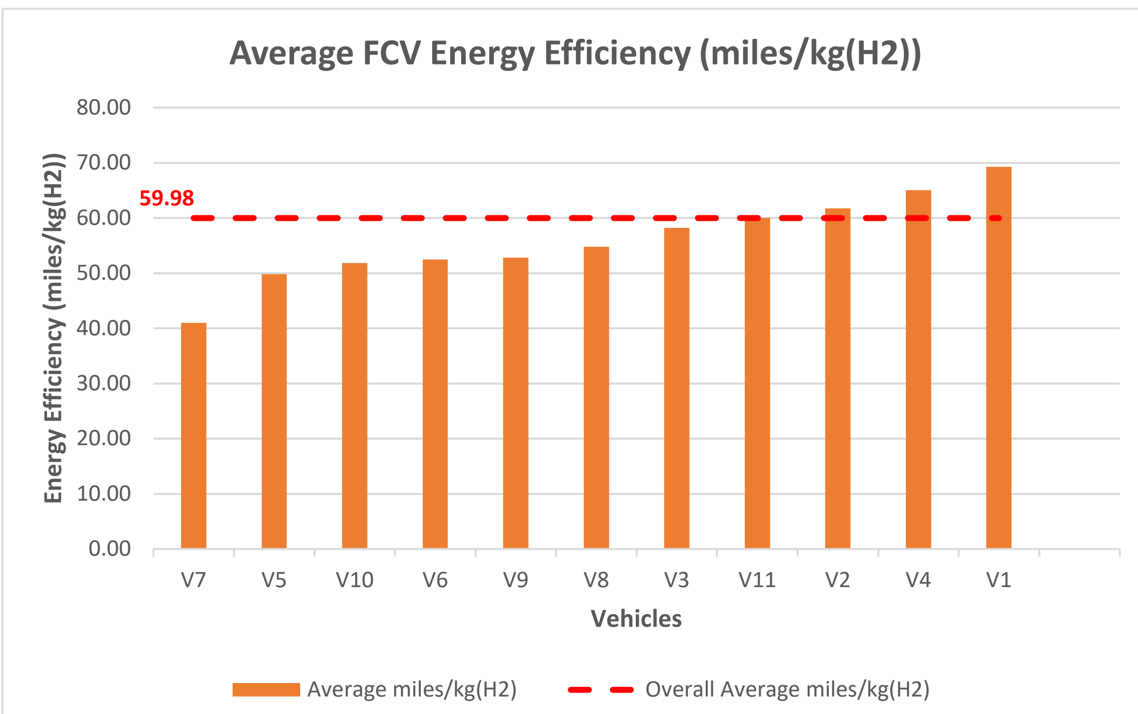


Figure 102. Average FCV Energy Efficiency (miles/kg(H2)

Figure 101 presents the average daily VMT of individual Mirais while **Figure 102** shows the average energy efficiency of the vehicles. Only 4 out the 11 Mirais had an average daily VMT higher than the fleet average of 35 miles. The fleet average efficiency of the vehicles was around 60 miles per 1 kg of hydrogen. While most vehicle noted average efficiencies that were fairly close to the fleet average, some vehicles recorded efficiencies far lower than the fleet average. V7 showed a particularly low efficiency of just around 40 miles per kg of hydrogen; this observation could be attributed to the fact that over 70% of V7's VMT is covered at speeds over 45 mph, according to **Figure 97**. Vehicles that use an electric motor to power themselves tend to be more efficient at low to medium speeds, so a greater frequency of high-speed driving can lower the average efficiency of these cars.

6.2 Fuel Cell Vehicle Refueling

Table 28 and **Figure 103-Figure 109** provide descriptive summaries of Mirai refueling patterns captured by data collected from the loggers. Refueling events were identified from significant increases in hydrogen level between trips. Refueling events were matched to fueling stations using the GPS coordinates at the end of the trip preceding the refueling event. Over 90% of refueling events had GPS coordinates within 100m of a known hydrogen fueling station, and over 96% could be matched to a fueling station within 200m. No refueling events matched multiple stations. Mirai refueling summary statistics are presented in **Table 28**. **Figure 103** illustrates the distribution of the time elapsed between the refueling events of all vehicles while **Figure 104** displays the distribution of the distance traveled between the events. About 70% of refueling events occur within a week after their immediately preceding refueling event and around 80% of the events occur after covering distances of over 100 miles (32% of the vehicle's range of 312 miles) from their preceding refuel.

Table 28. Refueling Summary

	Average Sessions/Day	Average kg(H)/Day
Days within Logging Window	0.08	0.17
Days when the FCV Refueled	1.02	2.59

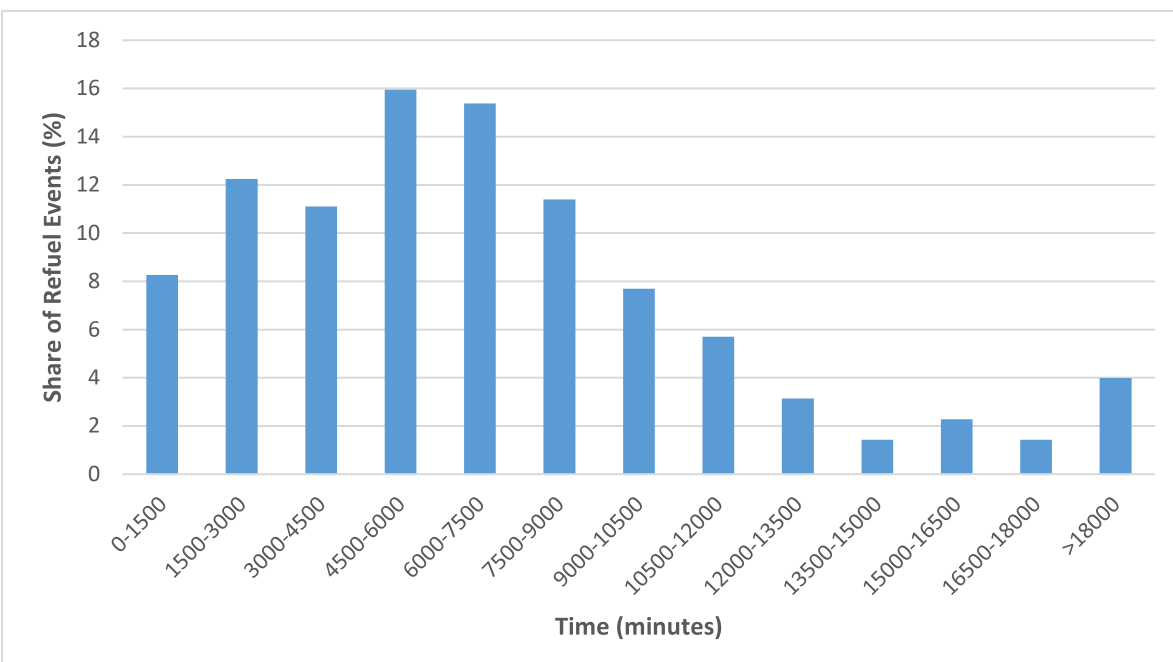


Figure 103. Time (in minutes) Elapsed between Refuels

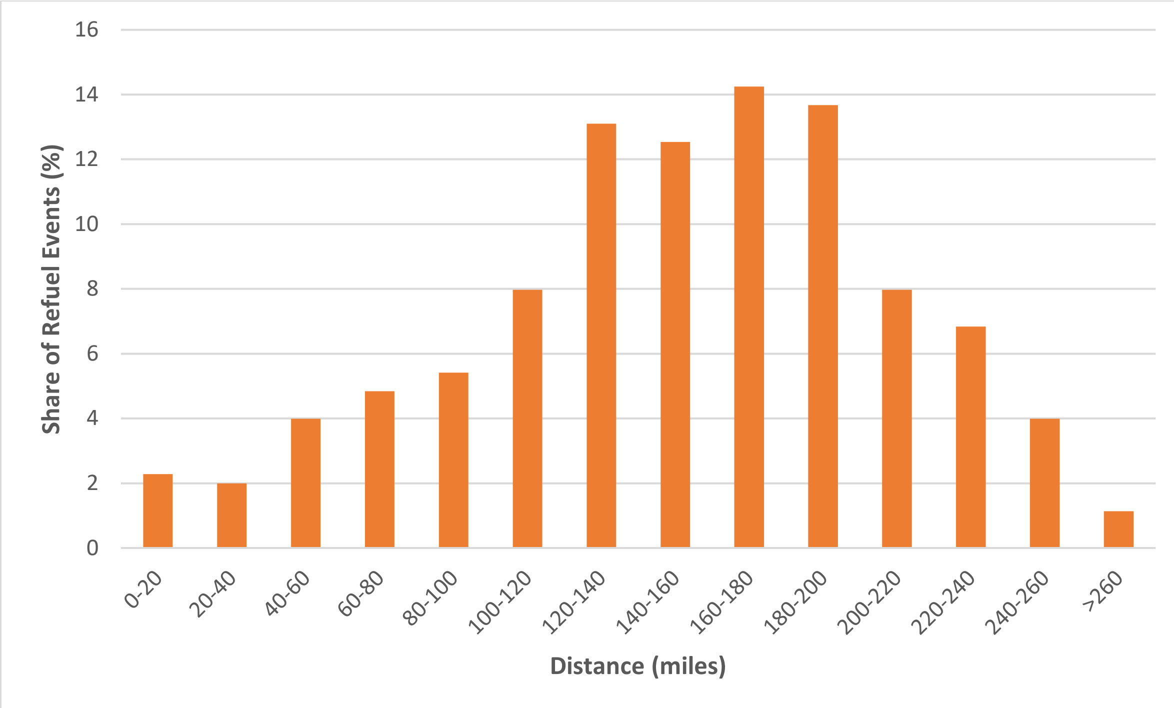


Figure 104. Distance Traveled Between Refuels

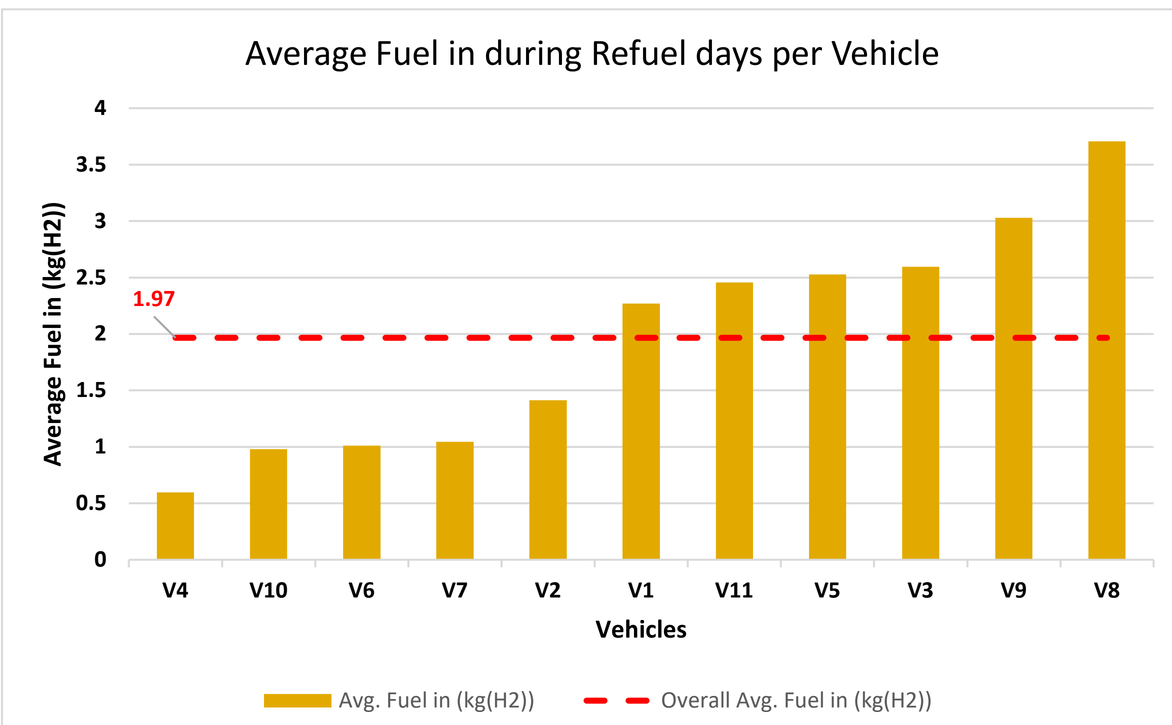


Figure 105. Average Fuel in during Refuel Days per Vehicle

Figure 105 displays the average fuel in during refuel days for each vehicle. While on average Mirai drivers seem to fill their tank with around 1.97 kg of hydrogen on refuel days, there seems to be a wide variation in refuel behavior. Some drivers seem to top off their tanks while others seem to wait to fill up their tanks after covering a significant amount of distance. V8 and V9, on average, wait until over 60% of their fuel is consumed before refueling. This variation could be linked to the distance between the typical trip origin/destination sets of these vehicles and the hydrogen stations that they frequent; further analysis is required to assess this connection.

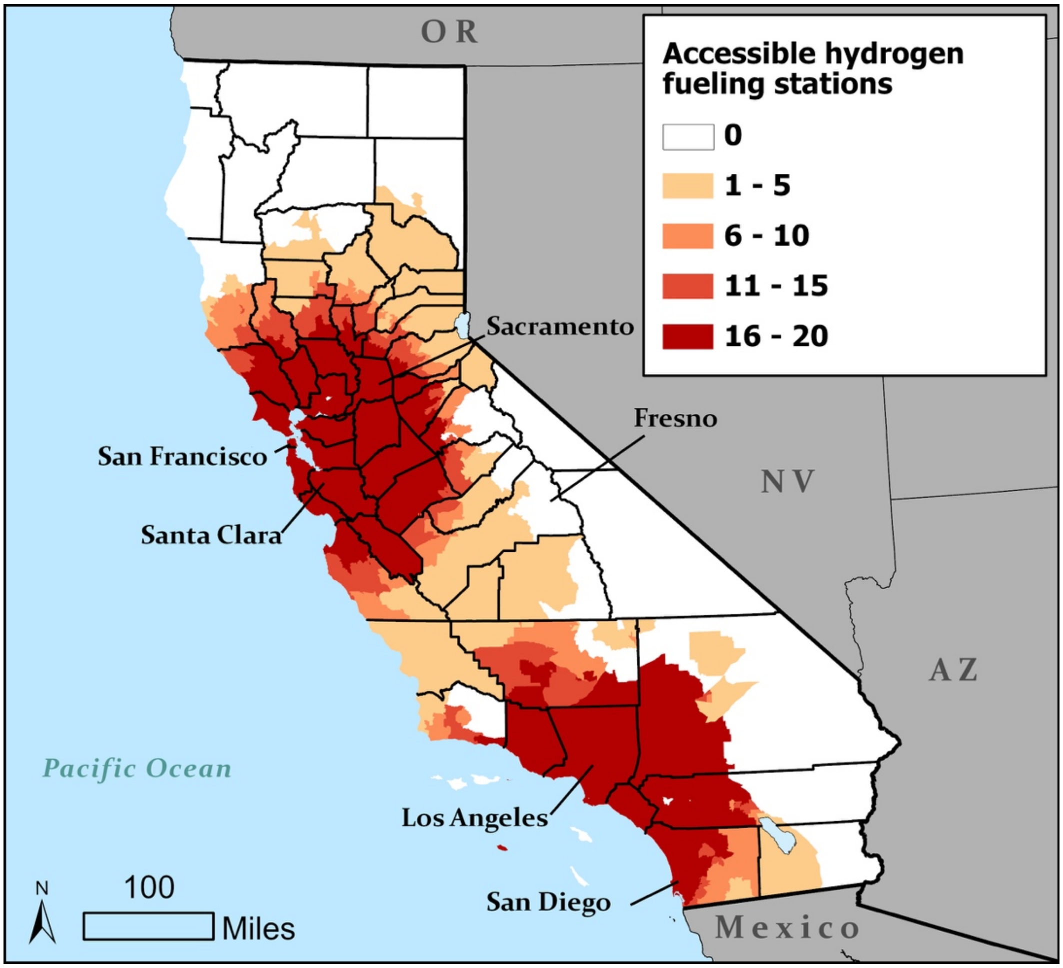


Figure 106. Number of Accessible Hydrogen Fueling Stations within 140 Miles of Each Block Group

Figure 106 captures how many hydrogen stations that are open to the public are accessible from each block group within the range of half a tank of a Mirai FCV. There seems to be a high to moderate concentration of accessible public hydrogen stations around areas (colored in red to beige), surrounding major metropolitan areas i.e. San Francisco and Los Angeles. On the other hand, the regions to the far north and far east of the state (colored in white) have no public stations that can be reached on half of a fuel tank when driving a Mirai, constraining the travel radius of FCV drivers that enter those regions.

Figure 107. Areas within 5 and 10 Miles from a Refueling Station

Figure 107 visualizes the areas that are less than 5 and 10 miles away from a public hydrogen refueling station. There seem to be a limited number of areas that have public hydrogen refueling stations within a 10-mile radius. The areas are mostly clustered around the state's major metropolitan regions (San Francisco, Los Angeles, Sacramento, etc.). However, since most of the state does not have accessible hydrogen stations within a 10-mile driving distance, it potentially plays a role in dissuading drivers from investing in FCVs.

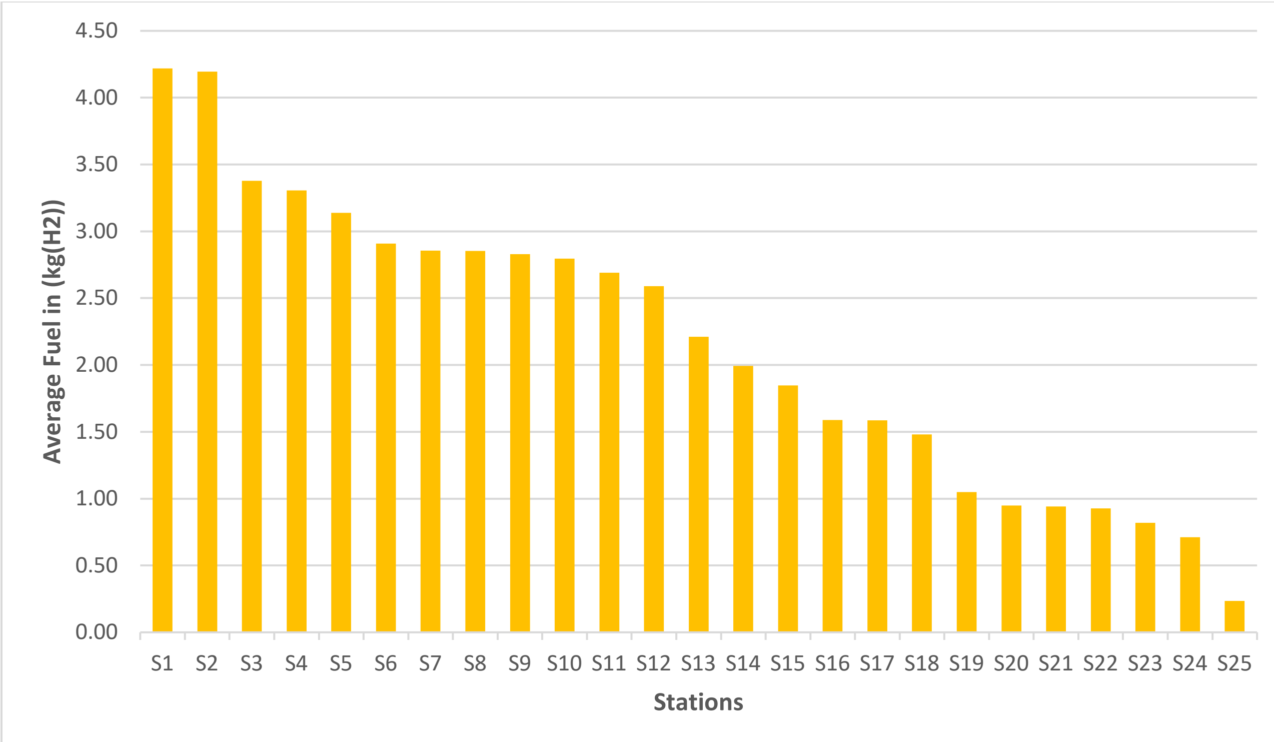


Figure 108. Average Fuel pumped in during Refuel, per Station

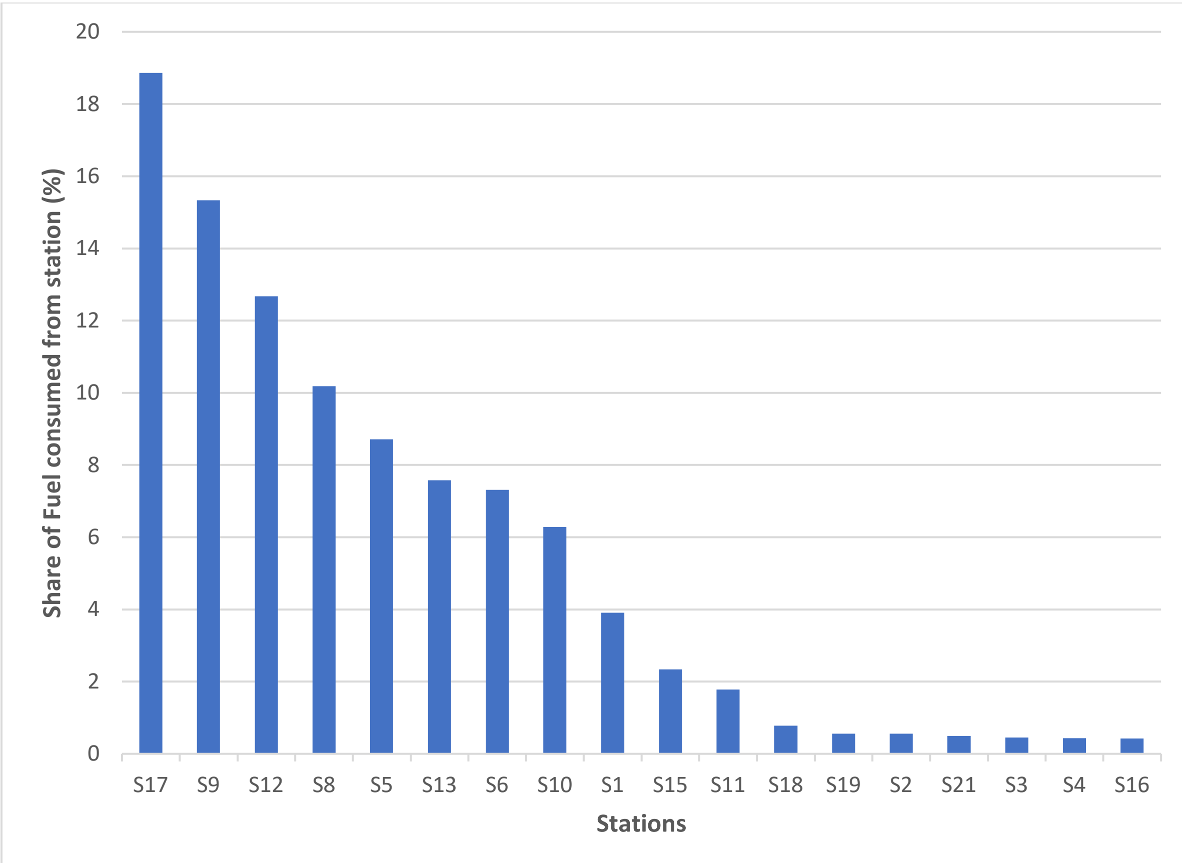


Figure 109. Refueling Share per Station

Figure 108 shows the average fuel during a refuel for individuals at hydrogen stations while **Figure 109** presents the share of refuels per hydrogen station. Majority of the refuels seem to take place at 10 out of the 25 stations visited by the vehicles in the dataset. This could be attributed to the fact that there are a lot of missing refuel events due to a high proportion of missing fuel level data for some cars as mentioned earlier. Of these 25 stations, 11 are in Los Angeles County (stations 2, 3, 4, 5, 6, 10, 12, 18, 19, 24, and 25), 7 are in Santa Clara County (1, 8, 9, 13, 14, 16, and 17), 4 are in Orange County (7, 11, 15, 21), and one each are in Fresno (20), San Diego (22), and Ventura (23) counties.

6.3 Fuel Cell Household Analysis

Our dataset contains 11 FCV households with 4 Mirai-only households, 6 single ICEV Mirai household and one double ICEV Mirai household. The double ICEV household was dropped from this analysis due to low sample size. Seven of these households are in the San Francisco Bay Area and four are in the Los Angeles Area. **Table 29** summarizes the (average) annualized estimates of key FCV metrics at the household level. The metrics include eVMT, gVMT, HH VMT, UF and energy consumption. **Figure 110** presents the HH UF of individual FCV households. The UF of individual Mirai households ranged from 0.47 to 0.83 with an average of 0.65. **Figure 111** shows the average daily HH VMT and the share of eVMT, gVMT in FCV HHs.

Based on **Figure 111** that plots the average VMT of individual households, households with higher daily average VMT (>40 miles) tend to have high UF; this can be observed in HH6, HH8 and HH10.

Table 29. (Average) Annualized Estimates of VMT and Energy Consumption on FCV HHs

HH Type	Num HHs	FCV Trips	FCV eVMT	FCV Hydrogen Consumed (kg)	ICEV gVMT	ICEV Fuel (gallons)	HH VMT	HH UF
ICE-FCV	6	1282	9892	139	5337	250	15229	0.65
FCV	4	1171	10620	190	0	0	10620	1

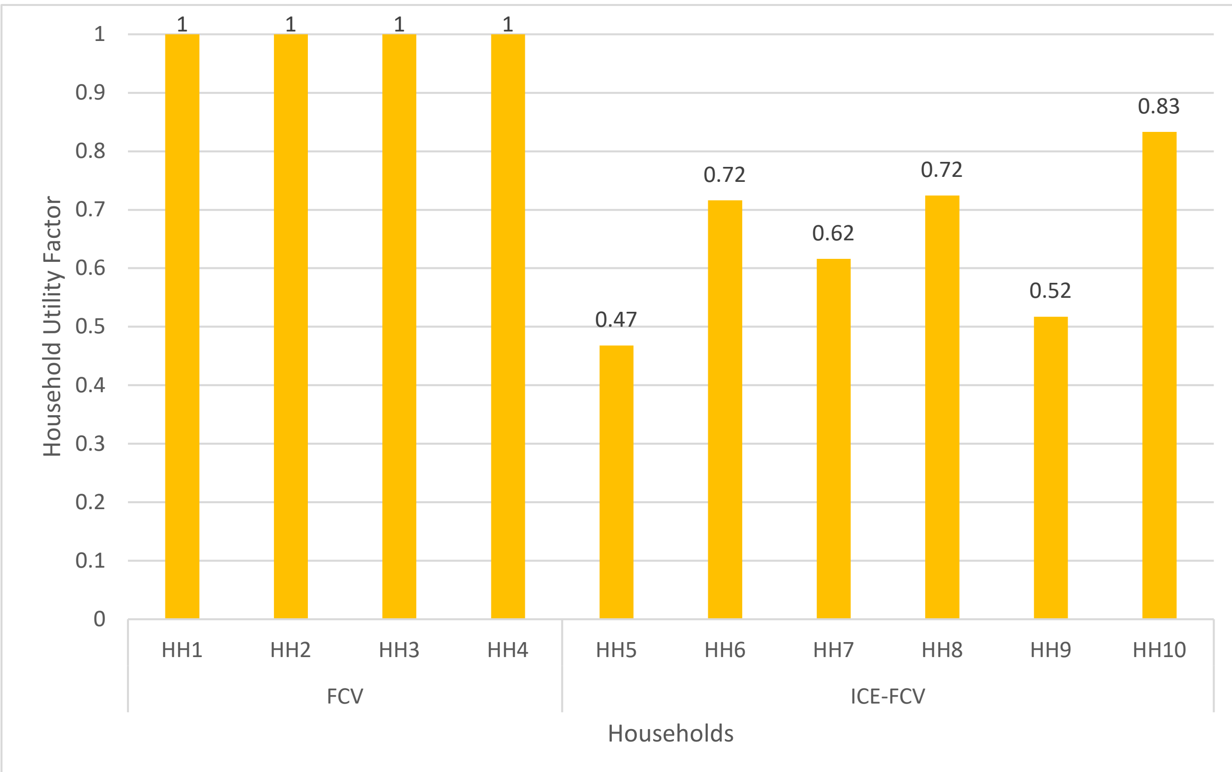


Figure 110. Household Utility Factor per Vehicle by Household Car Composition

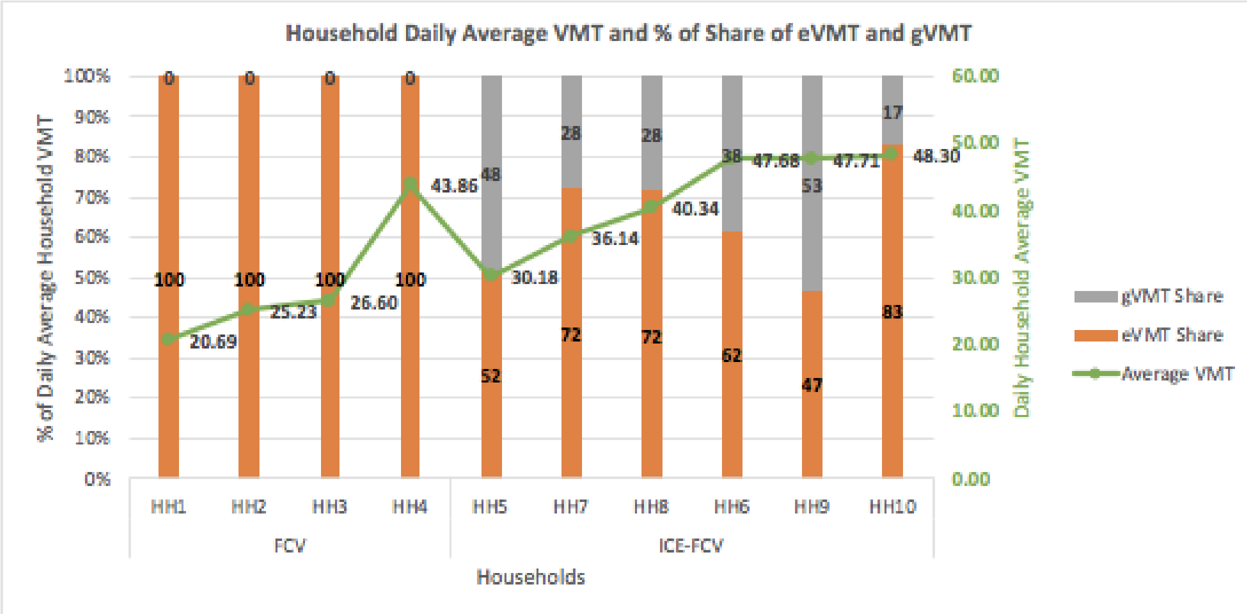


Figure 111. HH Average Daily VMT in HHs with FCVs, Showing the eVMT and gVMT Percentages

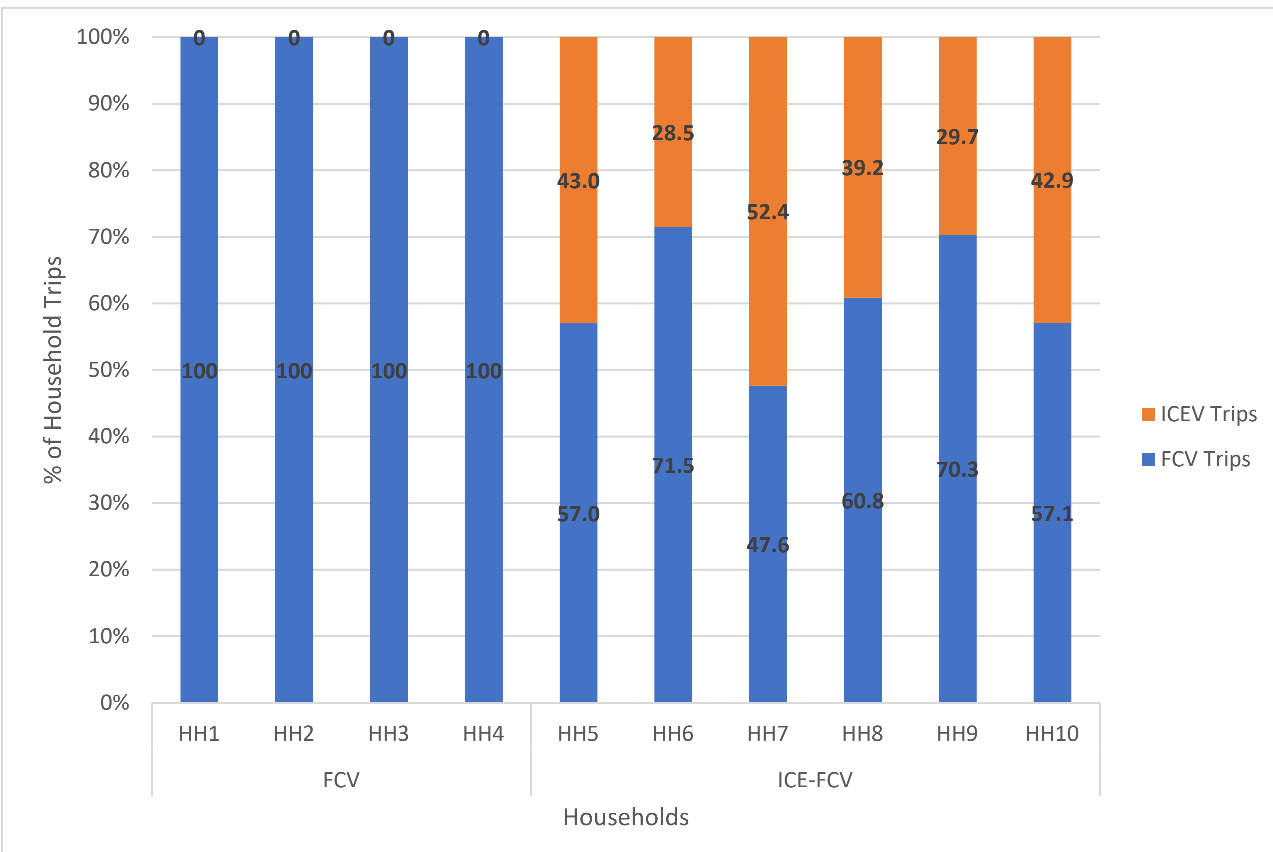


Figure 112. Percentage of FCV and ICEV trips in HHs with FCV

Figure 112 depicts the percentage of HH trips taken using the FCV and the ICEVs. On average, FCV share of HH trips was approximately 61% for the two car HHs. HHs that reported high UFs did not necessarily have high ratio of FCV trips to ICEV trips. For instance, HH7 and HH10 showed relatively high UF but they have relatively low ratio of FCV to ICEV trips (less than 57%), suggesting that some HHs are using their FCVs for trips covering longer distances.

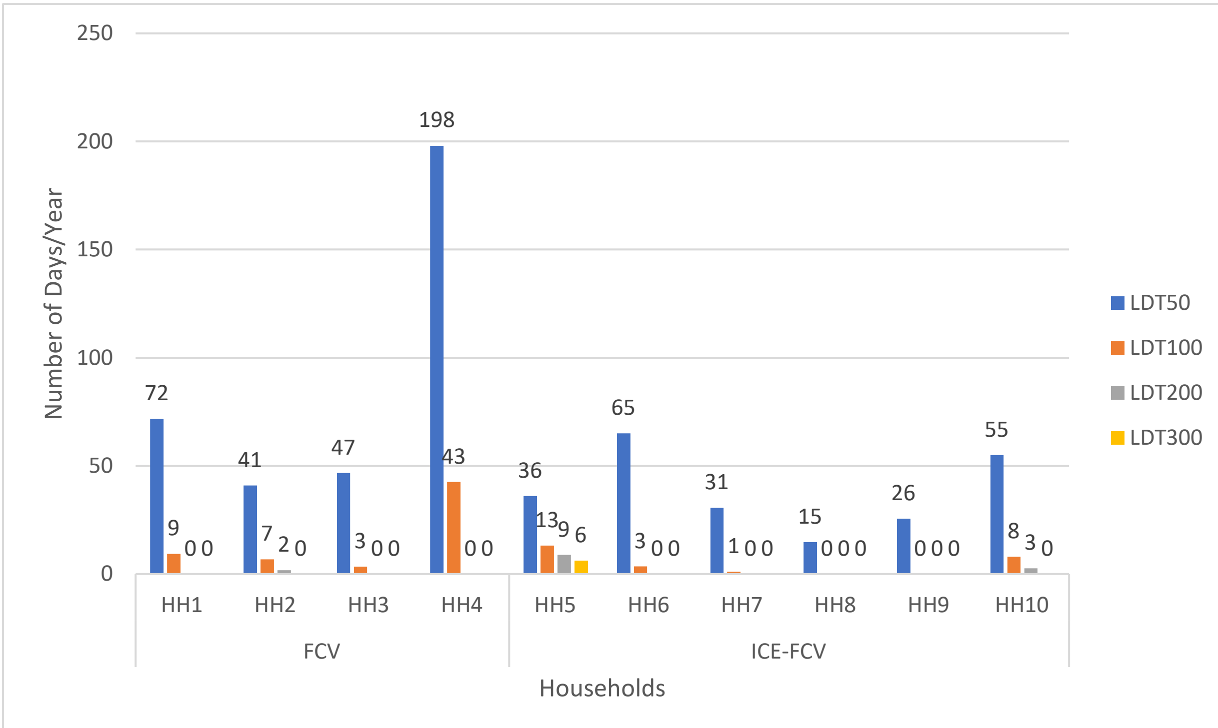


Figure 113. Number of Days/Year FCV was Used for Long Distance Travel (LDT).

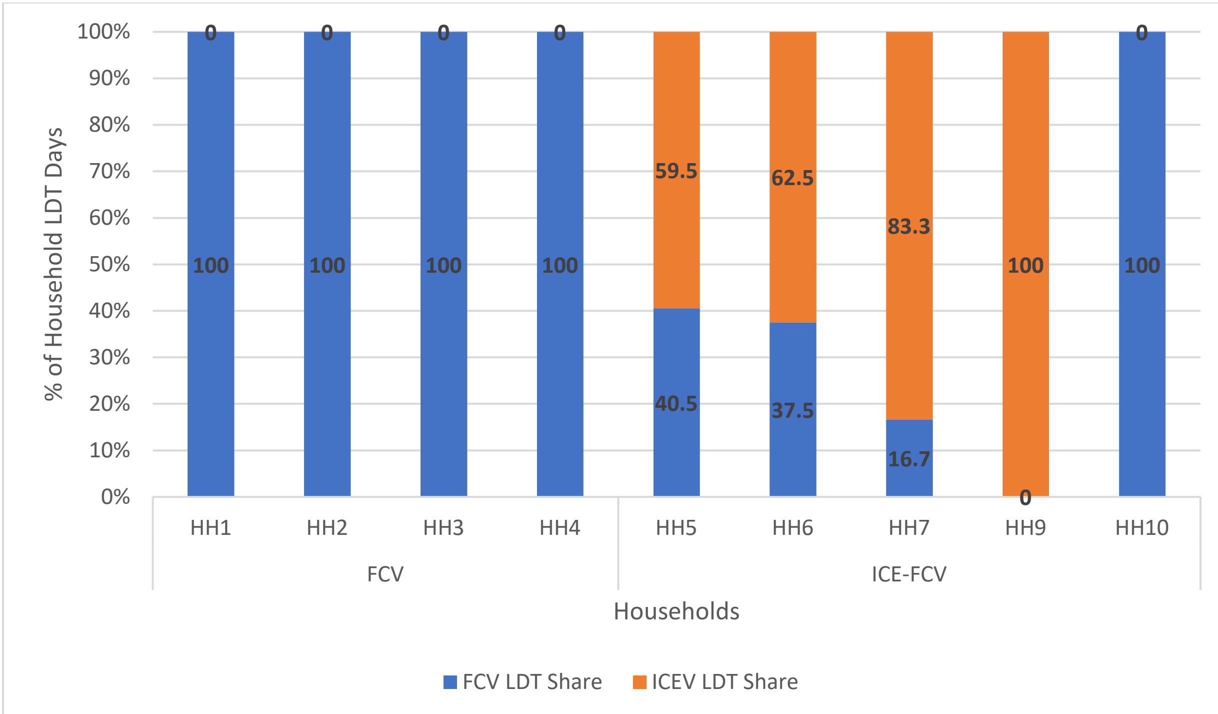


Figure 114. Percentage of FCV and ICEV LDT (>100 mi) Days over LDT Days in HHs with FCV

Figure 113 shows the absolute number of days the FCVs were used for LDT while **Figure 114** shows the ratio of FCV and ICE LDT (over 100 miles) days. As expected HH7 and HH10 which showed relatively high UFs and low FCV to ICE trip ratios, have a substantial proportion of FCV LDT days. On the other hand, HH9 which had a relatively low HH UF and high FCV to ICE trip ratio, covered all its trips exceeding 100 miles in the ICE.

7 Workplace Charging and Out of Home Charging: Lessons from In-depth Interviews

The data for this section is from forty semi-structured qualitative interviews that were conducted with PEV drivers across California. The interviews explored driver commute information, charging behavior, and experiences with charging etiquette (see Appendix 1 for the topics explored in the interviews). Interviews lasted on average 45 minutes and were conducted at the interviewees' homes. Interviewees were selected based interviewer's availability and the driver's willingness to share their experiences. Only forty interviews were conducted because that was when saturation occurred, and no innovative ideas were being put forth. This section aims to uncover how workplaces manage charging to increase the utilization of charging stations, and to understand drivers' experiences with them. We can then recommend improved techniques to maximize the utilization of charging infrastructure at work. By managing how people charge at work, more people can use the workplace chargers per day, meaning fewer chargers are needed to support a larger number of PEVs, and more vehicles can be driven on electric miles. Workplace charging stations can be seen as a scare resource when improperly managed due to their limited availability. Appropriately managed workplace charging can alleviate congestion and increase the availability of the scarce resource. Some workplaces may experience charging station stagnation if there is no motivation to move the vehicle when it has done charging. Conversely, if there was higher turnover of vehicles per day, fewer chargers would be needed to meet demand. Workplaces who are considering installing chargers can use this research to plan charging stations locations with maximum benefits for charging vehicles and minimizing charging congestion. Compared to home-based charging, workplace charging stations can support a higher number of PEVs with a lower amount of stations which can reduce infrastructure investment costs.

7.1 Introduction to Charging Management Strategies

Here we define three terms used throughout the section, these are charging congestion, charging station stagnation, and charge management strategies. Charging congestion is defined as a greater number PEVs wanting to charge than available electric vehicle chargers for those vehicles. This generally means PEV owners are unable to charge or must wait to access a charger. Charging station stagnation is when a PEV plugged into the charger has completed charging and the owner has not made the charger available to other PEV owners, either due to not moving their vehicle or unplugging the charge outlet. This can exacerbate the issue of charging congestion and can lead to chargers being underutilized. Finally, charging management strategies are any rules aimed at reducing stagnation and congestion, which results in higher utilization of chargers. These rules could be formal or informal, and may include time restrictions, pricing, formalized queuing, or anything else.

7.2 Methods

The data for this section was collected from drivers across California, which were selected from the households that participated in logged study and survey, in the summer of 2018. The interviews explored driver commute information, charging behavior, and experiences with charging etiquette. Interviews lasted on average 45 minutes and were conducted at the interviewees' homes. Interviewees were selected based interviewer's availability and the driver's willingness to share their experiences. Forty interviews were conducted because that was when saturation occurred, and no innovative ideas were being put forth. All interviews were then transcribed and coded in NVIVO software package.

This section focuses on a subset of forty drivers from the vehicle logger project who were part of the study in 2018 and who agreed to be interviewed.

There is potential for selection bias in the sample as interviewees had previously agreed to and participated in this project. We reached topical saturation with a diverse sample (geographically, by PEV type, by house type, etc.), shown in **Table 30** below, leads us to believe the interviews detect the most common charging management strategies currently employed.

7.3 Results

7.3.1 Interviewee Descriptions

The PEVs discussed are as follows: four Nissan Leaf (9%), fifteen Tesla Model S (35%), six Ford C-Max (12%), three Ford Fusion (7%), sixteen Chevrolet Volt (35%), and three other vehicles (5%) (one Chevrolet Bolt, one Fiat 500e, and one Toyota RAV4 EV). There were 22 (47%) BEVs and 25 (53%) PHEVs in the study. There were 11 (28%) MUD drivers and 29 (73%) single-family household drivers. **Table 30** below has a full description of the households.

Table 30. Summary of Interviewee Information

Interview	Total # Cars	# of PEVs	PEV	Vehicle Style	# ICEs	MUD	Gender	Age	Region
1	1	1	Chevrolet Volt	PHEV	0	1	Male	19-29	Bay Area
2	2	1	Ford C-Max	PHEV	1	0	Male	30-39	Bay Area
3	2	1	Nissan Leaf	BEV	1	0	Male	40-49	Bay Area
4	1	1	Tesla Model S	BEV	0	0	Male	40-49	Bay Area
5	3	1	Tesla Model S	BEV	2	0	Male	50-59	Bay Area
6	1	1	Chevrolet Volt	PHEV	0	1	Male	19-29	Bay Area
7	3	1	Tesla Model S	BEV	2	0	Male	60-69	Bay Area
8	1	1	Chevrolet Volt	PHEV	0	0	Male	30-39	Northern California
9	2	1	Nissan Leaf	BEV	1	0	Male	30-39	Bay Area
10	2	1	Chevrolet Volt	PHEV	1	1	Male	30-39	Bay Area
11	2	2	Tesla Model S / Chevrolet Volt	BEV / PHEV	0	0	Male & Female	30-39; 30-39	Bay Area
12	2	1	Ford Fusion	PHEV	1	0	Male	40-49	Sacramento Area
13	1	1	Chevrolet Volt / Fiat 500e	PHEV / BEV	0	0	Male	50-59	Bay Area
14	1	1	Chevrolet Volt	PHEV	0	1	Male	30-39	Bay Area
15	1	1	Chevrolet Volt	PHEV	0	1	Male	30-39	Los Angeles Area
16	3	1	Tesla Model S	BEV	2	0	Male	40-49	Los Angeles Area
17	2	1	Tesla Model S	BEV	1	0	Male	50-59	Los Angeles Area
18	2	2	Ford C-Max / Chevrolet Volt	PHEV / PHEV	0	0	Male	30-39	Los Angeles Area
19	2	1	Chevrolet Volt	PHEV	1	1	Male	30-39	Los Angeles Area
20	2	2	Chevrolet Volt / Nissan Leaf	PHEV / BEV	0	0	Male & Male	40-49; 50-59	Los Angeles Area

Interview	Total # Cars	# of PEVs	PEV	Vehicle Style	# ICEs	MUD	Gender	Age	Region
21	1	1	Tesla Model S / Toyota RAV4 EV	BEV / BEV	0	0	Male	40-49	San Diego Area
22	2	1	Chevrolet Volt	PHEV	1	0	Male	50-59	Bay Area
23	2	1	Tesla Model S	BEV	1	0	Female	50-59	Bay Area
24	1	1	Chevrolet Volt	PHEV	0	1	Male	40-49	Los Angeles Area
25	3	1	Tesla Model S	BEV	2	0	Male	50-59	San Diego Area
26	1	1	Chevrolet Volt	PHEV	0	1	Female	40-49	Los Angeles Area
27	2	1	Tesla Model S	BEV	1	0	Male	40-49	Los Angeles Area
28	2	1	Ford Fusion	PHEV	1	0	Male	30-39	San Diego Area
29	2	2	Nissan Leaf / Chevrolet Bolt	BEV / BEV	0	1	Male & Female	50-59; 40-49	San Diego Area
30	2	2	Chevrolet Volt / Ford Fusion	PHEV / PHEV	0	0	Male	50-59	San Diego Area
31	2	1	Tesla Model S	BEV	1	0	Male	40-49	Los Angeles Area
32	1	1	Tesla Model S	BEV	0	0	Male	70-79	Sacramento Area
33	2	1	Tesla Model S	BEV	1	0	Female	60-69	Northern California
34	1	1	Tesla Model S	BEV	0	1	Male	30-39	Bay Area
35	4	1	Chevrolet Volt	PHEV	3	0	Female	19-29	Sacramento Area
36	1	1	Ford C-Max	PHEV	0	0	Male	19-29	Sacramento Area
37	2	1	Ford C-Max	PHEV	1	0	Male & Female	50-59; 40-49	Bay Area
38	1	1	Ford C-Max	PHEV	0	1	Male	30-39	Bay Area
39	2	1	Ford C-Max	PHEV	1	0	Male	40-49	Bay Area
40	4	1	Tesla Model S	BEV	3	0	Male	50-59	Bay Area

7.3.2 Charging Behavior

Interviewee charging behavior is discussed below because of its relevance to workplace charging management. First, we explore home charging, followed by public, and then workplace charging. Then we discuss workplace charging management in detail.

7.3.2.1 Home Charging

Thirty-five people charge their vehicles at home, ten are unable to, and two chose to not charge at home (**Figure 115**). The interviewees who charge at home cite convenience and low refueling cost as their main reasons behind this choice. Of those that live in MUDs, eight (73%) are unable to charge at home. The drivers who live in a MUD noted the nuisances of not having a garage or access to electricity at their parking spot. Of those who choose to not charge at home (a Tesla Model S and Nissan Leaf), the Tesla Model S charges exclusively at work, and the Nissan Leaf has no issues relying solely on public charging. The quotes below outline reasons why interviewees do not charge at home.

"I don't have a garage, so I have to do street parking and that ultimately means I don't charge my car when I'm at home" (Interview 01, Chevrolet Volt)

"With the free options there didn't really seem to me to be much need for that, um, and it's not inconveniencing me at the moment to do it the way I'm doing it. Umm so, yeah, I haven't seriously considered the charging at home" (Interview 03, Nissan Leaf)

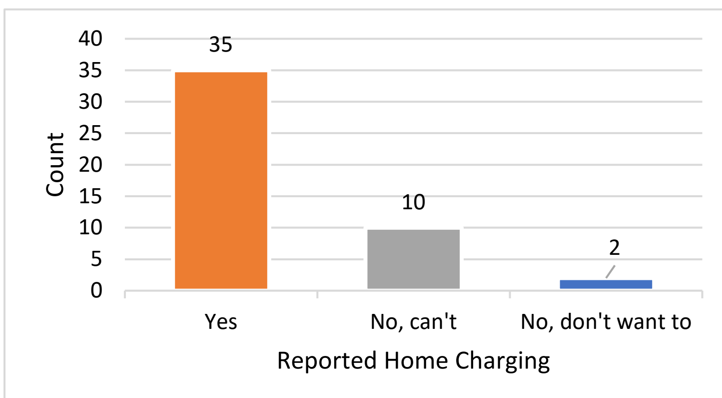


Figure 115. Interviewees reported home based charging (N=47)

7.3.2.2 Public Charging

Public charging is classified as charging that is not at home or while at work, as defined by (Lee, J.H. 2020) [5]. The frequency of charging in public is broken down by always, frequently, occasionally, rarely, and never (**Figure 116**).

Seven drivers reported always charging their vehicles when available in public. The vehicles include two Nissan Leafs, three Chevrolet Volts, one Chevrolet Bolt, one Ford C-Max, and two Tesla Model S. Of those seven, three are unable to charge at home. A few participants also mentioned that charging was a determining factor of where they travel.

"I also charge when I go shopping at the mall or the park, wherever there's a charging station… [charging] actually kind of skews on where I watch a movie, so … I just look at which one has more availability on charging stations and then that's where I go." (Interview 24, Chevrolet Volt)

Seven interviewees reported charging in public frequently. This was defined as those who would charge in public more likely than not when they go out. They may check the local EVSE they know for availability and may not mind adjusting their parking patterns to charge their vehicles. The vehicles in this category are two Chevrolet Volts, one Ford Fusion, one Ford C-Max, and three Tesla Model S. A few mention the secondary benefits of charging in public such as parking priority or saving money.

"Whenever we go out if there's a charger available well try to, to get it and just park there and you know, even if we have to walk a little extra, we'll do that" (Interview 08, Chevrolet Volt)

Sixteen drivers charge in public occasionally; from this sample, this is the largest segment. Occasional public charging interviewees were defined as those who know their routine charging stations, but do not seek out additional stations. As one interviewee put it, "*I don't really search for them. If they're there, they're there*" (Interview 02, Ford C-Max).

If it is convenient for them, they will charge their vehicle. The vehicles in this grouping are seven Chevrolet Volts, two Ford C-Maxes, five Tesla Model S, and two Nissan Leafs.

"I generally just try to charge it when I can when it's convenient for me. I don't want to go out of my way" (Interview 14, Chevrolet Volt)

Ten interviewees rarely charge in public. Five Tesla Model S, one Ford Fusion, three Chevrolet Volts, and one Ford C-max are part of this group. These drivers only use public charging as a last resort or very infrequently.

"Public chargers are literally for emergency use cause especially since I have it at home, like I just don't need to use public chargers" (Interview 27, Tesla Model S)

One interviewee with a Ford C-Max does not charge in public. He cited the hassle of charging compared to home charging and time to charge as preventing him from seriously considering using it.

"I don't go that many places where I would have time to charge my car" (Interview 37, Ford C-Max)

Irrespective of public charging frequency, seven drivers only charge in public when it is free (**Figure 116**). This is an additional grouping and is not a category of charging frequency. It contains two Ford C-Maxes, three Chevrolet Volts, and two Tesla Model S. Paying for charging is not always a disincentive for drivers to charge.

"I will only use a public charger if it's available and they're free" (Interview 23, Tesla Model S)

"There's a lot of them that are like paid um I don't usually bother using those um because we can do it at home and get the electricity from the solar panels" (Interview 34, Tesla Model S)

Some drivers had no problem paying to charge their vehicle or had a maximum amount they would pay to charge in public. Some find it useful to have a payment system to increase the chance of finding a vacant charging station. A few PHEVs mention the emissions offset from driving on electric while others want to support the EVSE companies by charging when they can.

"If you have to pay, then there's better turnover. And I can usually find a place to charge." (Interview 12, Ford Fusion)

"We always have gas but I hate oil. So, we try to avoid it as much as we can." (Interview 38, Ford C-Max)

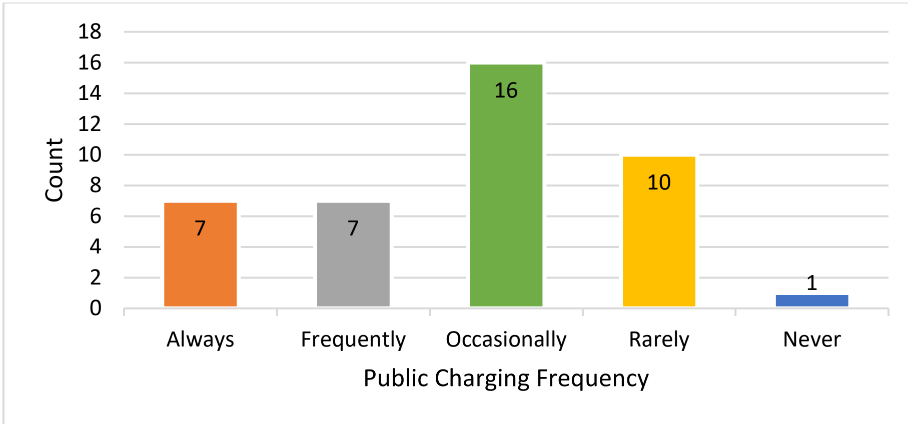


Figure 116. How often interviewees reported charging their vehicles in public (N=40).

7.3.2.3 Workplace Charging

Workplace charging is defined as where people charge while they are working. Some workplace charging locations are in public lots; interviewees perceive this as workplace charging as it is where they park their car while at work. This definition is consistent with Lee et al. (Lee, J.H. 2020) [5]. Seventeen interviewees reported always charging their vehicle at work, six charged sometimes, five had the option to charge at work and chose not to, and seven had no access to charging at work. An additional nine interviewees were either retired, did not commute, or had an irregular driving schedule with no regular commute location so they cannot charge at work (**Figure 117**).

Seventeen interviewees reported charging their vehicles at work whenever there is an available charging station. The vehicles are ten Chevrolet Volts, two Ford C-Maxes, two Tesla Model S, one Ford Fusion, one Nissan Leaf, and one Chevrolet Bolt. The main motivator to charge at work was cost-savings and convenience. Free workplace charging meant that some interviewees prioritized charging at work over charging at home. Ten MUD drivers (of 11 interviewed) always charge at work. Some drivers reported wanting to charge every day but were unable to because of charging station congestion. Some reported driving in earlier or later (after lunch when others would move their vehicle) to ensure they would be able to access a charging station.

"It was kind of in the middle of a big parking garage that was a little bit further away, um but that was totally fine" (Interview 10, Chevrolet Volt)

"I charge at work because it's free. It's convenience." (Interview 11, Tesla Model S)

Six interviewees in the sample charged at work sometimes. These interviewees include two Tesla Model S, one Nissan Leaf, one Ford Fusion, one Ford C-Max, and one Toyota RAV4 EV owning households. These drivers used workplace charging as secondary to home charging. They would sometimes charge at work because they needed additional charging because they forgot to charge at home or drove additional miles beyond their normal routine. Some interviewees reported charging at work because the parking space was in a better location than the non-charging spaces.

"The reason we'd charge at work is that someone forgets to plug it [the household's BEV] in it at night. That's the primary reason like, "oh!" Or if she's running errands during the day and just needs a quick charge to get home." (Interview 09, Nissan Leaf)

Five interviewees do not charge at work; the vehicles owned by these interviewees are three Tesla Model S, one Nissan Leaf, and one Ford C-Max. Some drivers find workplace charging inconvenient because the EVSE was too far from their office, due to cost, or because the charging management strategies did not align with their schedule. One PHEV driver chose not to charge at work to keep the spaces open for BEVs owners who may need to charge.

"[Work] has charging stations, but it's a dollar an hour, and you have to move your car every 2 hours so that's very inconvenient." (Interview 33, Tesla Model S)

Seven interviewees reported being unable to charge at work. These include those who own the following vehicles: one Fiat 500e, three Chevrolet Volts, two Ford C-Maxes, and one Tesla Model S. Reasons for this include having no charging infrastructure installed or parking being too much of a luxury to dedicate to charging at their workplace.

"We don't have any outdoor outlets on our building. And even if we did, you would have to drape the cord across sidewalks and planters, across parking lots, so, um, it's just not practical and not worth it." (Interview 22, Chevrolet Volt)

Nine interviewees do not commute, have an irregular commute, or are retired. These people are excluded from the workplace sample because their travel patterns do not allow them to charge at a workplace.

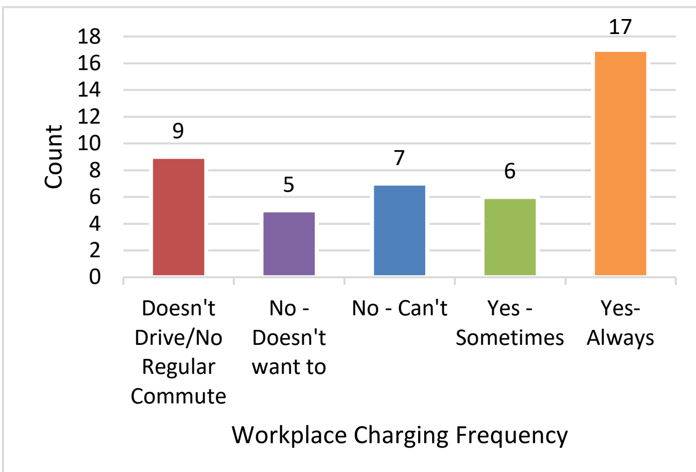


Figure 117. Break down of interviewee's work charging patterns and availability. Nine interviewees did not have a regular commute or were retired. (N=44)

7.3.3 Workplace Charging Management Strategies

Twenty-three (58%) interviewees reported charging at work either every day or sometimes while five people said they have the option to charge at work, but do not (**Figure 118**). Twenty-six of these 28 interviewees provided information on charging management strategies at their workplace charging location. From these interviewees, three categories of approaches were detected. We refer to these as 'authoritative charging management strategies', 'collective charging management strategies', and 'unmanaged charging'.

7.3.3.1 Authoritative Management Strategies

Twelve interviewees reported having a set of rules enforced and created by their workplace, which we call ‘authoritative charging management strategies’. These are rules that have been applied to workplace charging by the company, without input from the charging station users.

Reported authoritative management strategies include digital queuing, rotation, a time limit with pricing, and valet charging. Digital queuing occurs when one vehicle is charging and a second parks next to it waiting to charge. This required having more parking sports surrounding the EVSE than there were ports. The driver of the second vehicle taps a card (in this case a ChargePoint card) against the reader to get in the virtual queue to use the charging station. When the first vehicle has finished charging, the second driver is notified via email that they can unplug the first vehicle and plug in their vehicle. Rotation is defined as the company forcing the driver to move their vehicle after a time limit or the vehicle has completed its charge; this information is usually conveyed in the form of signs or digital messaging. Non-compliance can lead to a penalty. These are not independent strategies: one workplace could employ multiple strategies.

“[There is] a rotation system where you, since there are more cars than there are charging spots, park next to charging station and you badge in and then whenever the car next to you is fully charged you get notified and then you go down and you switch the charger.” (Interview 01, Chevrolet Volt)

Time limit with pricing is when the system is set up to be free or exceptionally low cost, and after a set number of hours, the price ramps up significantly.

“If you keep your car charged for longer than 3 hours, then they uh start charging you like 5 bucks an hour. So that’s ah, it’s a real- it’s a strong incentive to move your car and let other people use it.” (Interview 19, Chevrolet Volt)

Valet charging was observed in workplaces that already had valet parking for their employees with EVSE in the lot. The valets are responsible for charging the vehicles and rotating them, as necessary. The two interviewees who had workplace valet charging were less aware of how their vehicle’s charging was being managed because they were not physically involved in the charging process. These interviewees were indifferent about how their vehicle was charged so long as it was ready for them upon leaving work. For workplaces in this sample who had valet parking for their employees, the charging was managed by the valet, and was paid.

“Valets are good about rotating the cars around, so everybody gets a charge and like, I’m usually charged up full by the time I go home” (Interview 18, Ford C-Max)

Eighteen (64%) workplaces required joining a charging network company before being able to charge. Requiring employees to have an EVSE membership (e.g. ChargePoint) does not qualify as authoritative management because no mechanisms to increase charger utilization were in place.

7.3.3.2 Collective Management Strategies

Four interviewees stated they and their fellow co-workers created rules for charging at work, known here as ‘collective management strategies’. These systems are organized by the employees who drive and charge their PEVs at work. These interviewees’ workplaces did not have any formal rules in place (i.e. Unmanaged Charging). Examples of collective charging management strategies include day restrictions (e.g. only being able to charge on Mondays and Wednesdays), time of day restrictions (e.g. a 4-hour limit on charging), messaging an email group when your vehicle is done charging, and well-maintained spreadsheets of vehicle owner contact information which could be used to request someone to move their vehicle. The vehicles in this category are two Chevrolet Volts and two Nissan Leafs.

Collective charging is only functional if there is a strong intent of commitment and leadership to get everyone's vehicle charged with a shared resource. One interviewee reported that their office's "leader" left the company, and it was proving difficult to pick up the pieces of their charging patterns. This technique only arises when there is unmanaged charging at work, and the collective wants to do something about it.

"I'm part of that google doc, so you know you have to coordinate with another person, go down and meet them, swap cars, um you know and then you have to check the doc 'cause someone may say I want it when you're done." (Interview 20, Nissan Leaf)

One interviewee (quoted below) stood out because they were collectively charging from an 110V outlet. Due to the inefficient time required to charge at this power level, it was it was unexpected that co-workers would justify time to create a schedule for them all to charge. This interviewee does live in an MUD without home-based charging, so this is one way he is able to charge his Chevrolet Volt.

"We just kind of had a meeting and said okay how can we best handle this without fighting for it?" (Interview 24, Chevrolet Volt)

7.3.3.3 Unmanaged Charging

Ten (38%) drivers reported no organization or rules for charging at work; we have classified these as 'unmanaged charging.' Drivers report there is often competition to charge and sometimes cannot charge if they arrive at work too late in the day. Two interviewees recently changed jobs and went from an authoritative management strategy to unmanaged workplace charging. They both reported frustrations with the lack of management for the EVSE. One even asked HR for some sort of managed charging but had not heard back.

"It's just like, you grab it, and it's yours all day. If you're going to be really nice you could move the car out and like, move to a different spot, but I usually don't have time during the day to do that." (Interview 10, Chevrolet Volt)

"Over the course of the past few years, as more electric vehicles have come to [work], it's become a little bit more challenging to make sure you get charge" (Interview 40, Tesla Model S)

Five interviewees report that they charge by bringing their own charging cord to plug into an 110V or 240V outlet at the workplace. Five people have charging at work with installed charging infrastructure that has no rules. Vehicles here include two Chevrolet Volts, three Tesla Model S, one Ford Fusion, one Nissan Leaf, one Chevrolet Bolt, and two Ford C-Maxes.

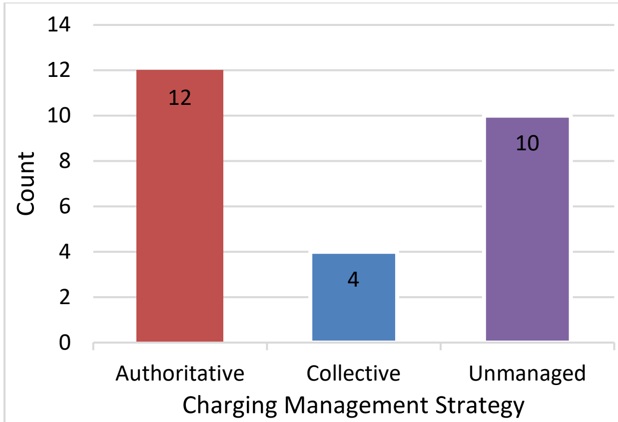


Figure 118. Three interviewees did not go into enough detail about their workplace charging management strategies to categorize (n=26)

7.4 sInterviews Discussion

Charging management strategies appear to be effective in increasing vehicle turnover at workplace EVSE. With higher turnover, more people can use the stations thus increasing their utilization and availability. This allows more PEVs to charge and reduce the number of EVSE a workplace may need to install. Most interviewees liked their workplace's authoritative charging management strategies. Four BEV owners chose to not charge at work. One has a collective charge management (messaging and moving vehicle when done charging), one has authoritative charge management (priced charging), and two did not give enough detail to classify (their lack of knowledge of the system indicative of the fact they never charge at work). Drivers can complete their travel without using the EVSE which leaves the stations available for others to use. The rules for those charging stations have the intended effect of increasing availability of EVSE and decreasing congestion. Decreasing congestion leads to a more reliable charging experience because drivers are more likely to be able to charge their vehicles when needed. Had they charged when they did not need to, they would have created unnecessary congestion to the workplace EVSE; charging management strategies are mitigating potential congestion. A few drivers stated that if the management strategies aligned better with their work habits, they would charge at work instead of or in addition to home.

Interviewees who were part of collective charging management systems also reported positive experiences. They liked designing their own rules to fit the needs to the drivers. These systems also increased the number of vehicles that could be serviced by the limited number of EVSE. Collective strategies were only found at workplaces with a small number of stations and PEV drivers; this could be because in a smaller office there can be more of a community mindset where the drivers interact more regularly. Collective strategies, however, may not be intuitive to newcomers and could be impeded by unaware drivers. Even a strategy designed by the drivers, for the drivers might not necessarily work for everyone.

For those without any charging management rules in place, drivers may not always be able to charge when they want or need. These workplaces may have underutilized charging stations, not necessarily due to high charging congestion, but a high charging station stagnation as the drivers have no incentive to move their vehicle when charging is complete. By increasing the availability of the EVSE, they can be used more frequently throughout the workday.

7.5 Interviews Policy Discussion

The charging management strategies presented in this section can be a good starting place for how companies can offer charging to their workforce. Without enforced charging management, stagnation and congestion can occur at the charging stations reducing the number of PEVs that charging stations can support. This in turn increases the number of EVSE that a workplace would need to install, which can increase costs.

From the interviewees' perceptions, it appears that digital queuing and time limit with pricing are the best received. With digital queuing, if the EVSE cord can reach multiple parking spots, then drivers do not have to move vehicles during the workday and have to re-park the vehicle. Time limit with pricing still allows drivers to obtain reasonable amount of SOC within the free time limit and motivates drivers to move their vehicle.

When designing the infrastructure layout, digital queuing should be kept in mind. We recommend considering more parking spaces around the EVSE and charge cords that can reach multiple parking spaces. This coupled with an electronic queue means drivers do not have to move the PEV when it has done charging, and others can plug their vehicle in when one is finished. A rotational system like this can reduce congestion and allow more vehicles throughout the day to charge. Locating chargers away from the front of the building can solve the issue of PEV owners charging just to get a good parking location. Keeping the stations visible, however, can help create awareness of the available charging infrastructure.

Another EVSE layout is to install slower charging stations in the front of the building and faster charging stations farther away; this can create an additional soft barrier from charging to save the charging stations for people who make need to charge for a longer time or have a larger battery to refuel. An alternative is to install costly faster chargers in the front of the building, and many free slower charging stations toward the back of the lot. People who need to refuel quickly can spend the money to charge swiftly and maintain a nice parking spot, but those who are just taking advantage of free electricity can choose to park further back.

For workplaces with existing unmanaged charging we recommend adding enforceability, cost, and/or idle fee components to the EVSE to spur vehicle turnover. Adding a reasonable cost to charging vehicles may help alleviate congestion from vehicles who otherwise could charge at home. A reasonable rate, such as a few cents over the cost of electricity in the area (at home), would in theory not dissuade MUD drivers who rely on workplace charging, since the electricity price would be cost comparable to what they would pay if they had access at home. The threat of banning people from charging if the rules are not followed may also be a strong motivator to honor the guidelines. Idle fees or a steep fee increase when the car is done are particularly useful turnover techniques because the driver would be monetarily charged when not receiving any electrical charge.

These charging strategies are intended for workplaces whose employees park locally. A driver who parks at a public transit station, for example, would struggle to move their vehicle during the workday. The ideal charging management strategy for those parking lots would be on a per kWh or on a per charging session paid scheme, this may mean drivers will only charge when they need to do so. Making sure any charging strategy design is simple and easy for the drivers to use is important.

8 Conclusions

This report encompasses the findings of two projects, presents the collection of data from alternative fuel vehicles in California, and incorporates the largest independent objective source reporting on vehicles' performance. The project includes five years of data collection from different vehicles that have no standardized protocol for on-board data reporting. Over these five years, loggers were installed on about 800 vehicles, including ZEVs and ICEVs. The result is the collection of 7 million miles of data, including 4.3 million miles that are collected from alternative fuel vehicles. The data includes second by second observations of energy consumption, driving conditions, charging engine operations, and more, which can serve as the basis for many more scientific publications and reports in the future. Results from this study provide insights on first and second generation PEVs and FCVs as well as the environmental impacts of their battery size, range, driving behavior, and charging/refueling behavior.

The data collected shows that longer-range BEVs and PHEVs with larger batteries had a greater substitution of gasoline miles with electric miles. BEVs, PHEVs, and FCVs are used for commuting at higher rates than those of the rest of the fleet. In addition, these vehicles tend to account for a higher share of miles than that of other household vehicles, however, FCVs and small, short-range BEVs are rarely used for long road trips. Among longer-range BEVs, the Model S was used for a higher proportion of freeway driving and utilized DC fast charging far from home much more frequently than the Bolt-60 was used in a comparable manner. Other than battery size variations, the difference in behavior of these two long-range BEVs can partly be attributed to the fact that the Model S has a wider available DC fast charging network in California. There are three types of DC Fast charging available in the state to date: Combined Charging System (CCS), CHAdeMO and Tesla Supercharger. While the Bolt-60 is only capable of charging via CCS, the Model S can charge using a Tesla supercharger or CHAdeMO with an adapter. According to the Alternative Fuels Data Center, there are approximately 1000 Tesla supercharger and CHAdeMO public charging stations currently available in California compared to just around 780 public CCS stations, making DC fast charging far more accessible to the Tesla than to the Bolt-60. Furthermore, the Model S is larger than the Bolt-60 and therefore, is more likely to be used for long distance trips.

Most modeling and early assumptions hypothesized that electric vehicle drivers would plug-in every night and start each day with a full battery, but our results show that charging every other night is more common for longer range BEVs or when driving less, while charging more than once a day is common for PHEVs. On average, the BEVs in our study charge less than once a day, including days when the vehicle was not used as expected. PHEVs in the study had lower utility factor values than found in EPA results, because of driving more and faster than expected. PHEV drivers with larger batteries charge their vehicles more when needed, achieve higher utility factors, and have many days with no engine starts at all.

Home charging and level 2 charging are the main sources of energy. DC fast charging is mostly near home, and only Tesla vehicles use DC fast charging often for longer trips. Level 1 charging was also significant for long, overnight trips. A sizable portion of users start charging events at midnight, regardless of utility rates. The interviews highlight the importance of charging policy and charging management in the workplace, where improving charger congestion, convenience, and dependability could increase usage.

The fuel cell vehicles in our study are mostly used in metropolitan areas where fueling stations exist. In interviews, FCV users report adjusting their driving needs based on long term experience with infrastructure reliability. FCV users do not drastically change their driving behavior in situations where infrastructure is unreliable, such as a station being out of order or there being an energy shortage.

Overall, longer-range PEVs have more electrified miles than their shorter-range counterparts, resulting in a reduced greenhouse gas (GHG) footprint. However, to maximize the benefits of PEVs, a full set of policies is needed to address charging behaviors and vehicle purchases. This study focuses on ZEV performance and household performance but did not collect data to compare those households to the general population and ICEV-only households. The results of this study address possible factors that affect the environmental impact of ZEVs. As those factors continue to change over time, ongoing research is necessary to better shape the policies that lead to more sustainable transportation and efficient ZEV usage.

9 Glossary

AE	all electric (a mode of PHEVs)
AER	all-electric range
BEV	battery electric vehicle
CDB	charge depleting blend
CS	charge sustaining
DCFC	DC fast charger
eVMT	electric vehicle miles traveled
FCV	fuel cell electric vehicle
GHG	greenhouse gas
gVMT	gasoline vehicle miles traveled
HDD	habitual driving distance
HH	household
HOV	high occupancy vehicle
ICEV	internal combustion engine vehicle
L1	Level 1 (refers to type of charger)
L2	Level 2 (refers to type of charger)
LDT	long distance travel
MPG	miles per gallon
MPGe	miles per gallon equivalent
MY	model year
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
SOC	state of charge
UF	utility factor

VMT	vehicle miles travelled
ZE	zero emission
zVMT	zero tailpipe emission trip

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11 Appendix A

Appendix 1 is a list of academic papers that uses data collected, by survey or loggers, as part of the Emerging Technology Zero Emission Vehicle Household Travel and Refueling Behavior (CARB Contract 16RD009) and Advanced Plug-in Electric Vehicle Travel and Charging Behavior project (CARB Contract 12-319).

1. Plug-in hybrid electric vehicle observed utility factor: Why the observed electrification performance differ from expectations

Authors: Seshadri Srinivasa Raghavan, Gil Tal

Publication date: 2020/11/13

Journal: International Journal of Sustainable Transportation

Publisher: Taylor & Francis

Description:

Plug-in hybrid electric vehicles (PHEVs) are an effective vehicle technology to reduce light duty vehicle greenhouse gas emissions and gasoline consumption. They combine all-electric driving capabilities of a battery electric vehicle with the engine downsizing and fuel economy improvements of a hybrid electric vehicle. Their environmental performance is predicated upon the metric utility factor (UF). It is formally defined in the Society of Automotive Engineers J2841 standard and denotes the fraction of vehicle miles traveled (VMT) on electricity (eVMT). Using year-long driving and charging data collected from 153 PHEVs in California with 11–53 miles range, this article systematically evaluates what aspects of driving and charging behavior causes observed UF to deviate from J2841 expectations. Our analyses indicated that charging behavior, distribution of daily VMT, efficiency of electrical energy…

2. Why do some consumers not charge their plug-in hybrid vehicles? Evidence from Californian plug-in hybrid owners

Authors: Debapriya Chakraborty, Scott Hardman, Gil Tal

Publication date: 2020/4/23

Journal: Environmental Research Letters

Publisher: IOP Publishing

Description:

The environmental benefits of plug-in hybrid electric vehicles (PHEVs) are closely related to the driving and charging behavior of vehicle owners. It is often wrongly assumed that PHEV drivers plug-in once per day. Using data from drivers of the vehicles we show this is not the case and that some drivers rarely charge their PHEV. If the vehicle is not plugged-in regularly, the vehicle will drive fewer electric miles and more gasoline miles, thereby losing out on potential emission savings. Analyzing 30-day charging behavior of 5,418 PHEV owners using a logistic regression model, we explore the factors that influence driver's decisions to not charge their vehicle. Several factors play a role in drivers' decision to plug-in their PHEV or not, including vehicle characteristics and the availability and cost of charging at various locations. Higher home electricity prices, lower electric driving range, lower electric motor power to …

3. Influence of User Preferences on the Revealed Utility Factor of Plug-In Hybrid Electric Vehicles

Authors: Seshadri Srinivasa Raghavan, Gil Tal

Publication date: 2020/3

Journal: World Electric Vehicle Journal

Volume:11

Issue: 1

Pages: 6

Publisher: Multidisciplinary Digital Publishing Institute

Description:

Plug-in hybrid electric vehicles (PHEVs) are an effective intermediate vehicle technology option in the long-term transition pathway towards light-duty vehicle electrification. Their net environmental impact is evaluated using the performance metric Utility Factor (UF), which quantifies the fraction of vehicle miles traveled (VMT) on electricity. There are concerns about the gap between Environmental Protection Agency (EPA) sticker label and real-world UF due to the inability of test cycles to represent actual driving conditions and assumptions about their driving and charging differing from their actual usage patterns. Using multi-year longitudinal data from 153 PHEVs (11–53 miles all-electric range) in California, this paper systematically evaluates how observed driving and charging, energy consumption, and UF differs from sticker label expectations. Principal Components Analysis and regression model results indicated that UF of short-range PHEVs (less than 20-mile range) was lower than label expectations mainly due to higher annual VMT and high-speed driving. Long-distance travel and high-speed driving were the major reasons for the lower UF of longer-range PHEVs (at least 35-mile range) compared to label values. Enhancing charging infrastructure access at both home and away locations, and increasing the frequency of home charging, improves the UF of short-range and longer-range PHEVs, respectively. View Full-Text

4. Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure

Authors: Jae Hyun Lee, Debapriya Chakraborty, Scott J Hardman, Gil Tal

Publication date: 2020/2/1

Journal: Transportation Research Part D: Transport and Environment

Volume: 79

Pages: 102249

Publisher: Pergamon

Description:

This paper examines the charging behavior of 7,979 plug-in electric vehicle (PEV) owners in California. The study investigates where people charge be it at home, at work, or at public location, and the level of charging they use including level 1, level 2, or DC fast charging. While plug-in behavior can differ among PEV owners based on their travel patterns, preferences, and access to infrastructure studies often generalize about charging behavior. In this study, we explore differences in charging behavior among different types of PEV owners based on their use of charging locations and levels, we then identify factors associated with PEV owner's choice of charging location and charging level. We identified socio-demographic (gender and age), vehicle characteristics, commute behavior, and workplace charging availability as significant factors related to the choice of charging location.

5. An in-depth examination of electric vehicle incentives: Consumer heterogeneity and changing response over time

Authors: Alan Jenn, Jae Hyun Lee, Scott Hardman, Gil Tal

Publication date: 2020/2/1

Journal: Transportation Research Part A: Policy and Practice

Volume: 132

Pages: 97-109

Publisher: Pergamon

Description:

We investigate the impacts of a combination of incentives on the purchase decision of electric vehicle buyers in California from 2010 through 2017. We employ a comprehensive survey on over 14,000 purchasers of electric vehicles in the state of California. The survey covers a swath of purchase intentions, general demographics, and importance of various incentives. Our results indicate that the most important incentives for plug-in electric vehicle (PEV) owners are the federal tax credit, the California state rebate, and high occupancy vehicle (HOV) lane access. In addition, the importance of the incentives and their associated effect on purchase behavior has been changing over time: respondents are less likely to not change their decision and more likely to not buy a vehicle at all as time passes and the technology moves away from early adopters. Incentives are becoming more important for vehicle adopters as PEV …

6. Factors Affecting Demand for Plug-in Charging Infrastructure: An Analysis of Plug-in Electric Vehicle Commuters

Authors: Gil Tal, Debapriya Chakraborty, Alan Jenn, Jae Hyun Lee

Publication date: 2020

Description:

The public sector and the private sector, which includes automakers and charging network companies, are increasingly investing in building charging infrastructure to encourage the adoption and use of plug-in electric vehicles (PEVs) and to ensure that current facilities are not congested. However, building infrastructure is costly and, as with road congestion, when there is significant uptake of PEVs, we may not be able to "build out of congestion." We modelled the choice of charging location that more than 3000 PEV drivers make when given the options of home, work, and public locations. Our study focused on understanding the importance of factors driving demand such as: the cost of charging, driver characteristics, access to charging infrastructure, and vehicle characteristics. We found that differences in the cost of charging play a key role in the demand for charging location. PEV drivers tend to substitute workplace charging for home charging when they pay a higher electricity rate at home, more so when the former is free. Additionally, socio-demographic factors like dwelling type and gender, as well as vehicle technology factors like electric range, influence the choice of charging location.

7. Demand drivers for charging infrastructure-charging behavior of plug-in electric vehicle commuters

Authors: Debapriya Chakraborty, David S Bunch, Jae Hyun Lee, Gil Tal

Publication date: 2019/11/1

Journal: Transportation Research Part D: Transport and Environment

Volume: 76

Pages: 255-272

Publisher: Pergamon

Description:

The public as well as the private sector that includes automakers and charging network companies are increasingly investing in building charging infrastructure to encourage the adoption and use of plug-in electric vehicles (PEVs) as well as to ensure that current facilities are not congested. However, building infrastructure is costly and, like road congestion, when there is significant uptake of PEVs we may not be able to "build out of congestion." Modelling the choice of charging infrastructure of more than 3000 PEV drivers who had the opportunity to select among home, work, and public locations, we focus on understanding the importance of factors driving demand such as: the cost of charging, driver characteristics, access to charging infrastructure, and vehicle characteristics. We find that differences in the cost of charging play a significant role in the demand for charging location. PEV drivers tend to substitute …

8. Incentives for Plug-in Electric Vehicles Are Becoming More Important Over Time for Consumers

Authors: Alan Jenn, Scott Hardman, Jae Hyun Lee, Gil Tal

Publication date: 2019/10/1

Description:

Federal and state governments are offering incentives to those who purchase or lease plug-in electric vehicles (PEVs), which include both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). Policymakers are beginning to consider the phase-out of these incentives and how a phase-out might impact PEV market growth. This brief highlights new research on the importance of incentives to consumers over time, based on survey data from 14,000 PEV-owning households in California between 2010 and 2017, collected and analyzed by the Plug-in Hybrid & Electric Vehicle Research Center at UC Davis. The PEV incentives included as part of this research are those currently available to Californian consumers: high occupancy vehicle (HOV) lane access; the US federal tax credit, which offers up to $7,500 to PEV buyers; and the California Clean Vehicle Rebate Project (CVRP), which offers $1,500 for a PHEV, $2,500 for a BEV, and an additional $2,000 for low-income consumers.

9. Who is buying electric vehicles in California? Characterizing early adopter heterogeneity and forecasting market diffusion

Authors: Jae Hyun Lee, Scott J Hardman, Gil Tal

Publication date: 2019/9/1

Journal: Energy Research & Social Science

Volume: 55

Pages: 218-226

Publisher: Elsevier

Description:

The successful market entry of plug-in electric vehicles (PEVs) is contingent on them being adopted by consumers, the first of which will be early adopters. The current understanding of these early adopters is based on small samples of PEV buyers gathered at one point in time. Here we present multi-year (2012–2017) questionnaire survey data on the socio-demographic profile of 11,037 PEV adopters in California. Latent class cluster analysis reveals four heterogeneous groups of PEV buyers. 49% are *High income families*, 26% *Mid/high income old families*, 20% *Mid/high income young families,* and about 5% are *Middle income renters*. Using the latent classes as input factors in Bass diffusion models we show that *high income families* may not continue to be the largest group of PEV adopters, while high income families are 49% of the PEV market today, they only represent 3.6% of California households. For …

10. An early look at plug-in electric vehicle adoption in disadvantaged communities in California

Authors: Kathryn Canepa, Scott Hardman, Gil Tal

Publication date: 2019/6/1

Journal: Transport Policy

Volume: 78

Pages: 19-30

Publisher: Pergamon

Description

Prior research on plug-in electric vehicle (PEV) adoption has revealed that early adopters tend to be wealthy consumers, this may mean that the benefits of PEVs are not being equitably distributed. Extensive research has shown that low-income and minority commutes are disproportionately impacted by environmental and transportation injustice. PEVs can contribute to importing air quality and could provide lower cost and more reliable transportation to low-income and minority communities if they are deployed there. This paper takes an early quantitative look at PEV adoption in disadvantaged communities (DACs), which are census tracts in California that suffer from a combination of economic barriers and environmental burden. We use six datasets to examine PEV market share, socioeconomic characteristics of PEV owners, and PEV charging infrastructure. Analysis confirms that adoption of both new and used…

11. An Examination of the Impact That Electric Vehicle Incentives Have on Consumer Purchase Decisions Over Time

Authors: Alan Jenn, Jae Hyun Lee, Scott Hardman, Gil Tal

Publication date: 2019/5/1

Description:

We investigate the impacts of a combination of incentives on the purchase decisions of electric vehicle (EV) buyers in California from 2010 through 2017. We employ a comprehensive survey on over 14,000 purchasers of EVs in California. The survey covers a range of purchase intentions, general demographics, and the importance of various incentives. Our results indicate that the most important incentives for plug-in electric vehicle (PEV) owners are the federal tax credit, the state rebate, and HOV lane access. In addition, the importance of the incentives and their associated effect on purchase behavior has been changing over time: respondents are more likely to change their decisions and to not buy a vehicle at all as time passes and the technology moves away from early adopters.

12. Characterizing Plug-In Electric Vehicle Driving and Charging Behavior: Observations from a Year Long Data Collection Study

Authors: Seshadri Srinivasa Raghavan, Gil Tal

Publication date: 2019

Source: Transportation Research Board 98th Annual Meeting Transportation Research Board

Issue: 19-03573

Description:

This paper analyzes driving and refueling/charging data using high-resolution GPS for plug-in electric vehicles (PEV) in households. This will help in understanding the energy efficiency and emission reduction associated with PEV usage. Consumer perceptions of PEVs' ability to meet driving needs as opposed to the ability of internal combustion engine vehicles may contribute to the low market share in the overall light-duty vehicle market. The results of this study can be used to help policymakers develop policies that encourage PEV adoption.

13. Exploring the Value of Clean Air Vehicles High Occupancy Lane Access in California

Authors: Wei Ji, Gil Tal

Publication date: 2019

Source: Transportation Research Board 98th Annual Meeting Transportation Research Board

Issue: 19-03755

Description:

This paper estimates the value of the California program that allows single-occupant use of high occupancy vehicle lanes by plug-in vehicles and to benefit from reduced tolls same as high occupancy vehicles. A survey was conducted that targeted PEV owners in California to understand their attitudes towards EV-related incentive policies, as well as their commute routes and the frequency of their access to high occupancy vehicle/toll (HOV/T) lanes. In San Francisco Bay Area for example, 32% reported that they are paying reduced tolls of about $540 dollars per year and 28% save on commute time while driving alone. The value of a program was estimated based on the toll savings reported and the value of travel time savings for each survey respondent while commuting, and the estimated value was compared with the corresponding Clean Vehicle Rebate for which the respondent was eligible. The authors also examined the spatial heterogeneity of CAV decal value across different regions and tested the impact of local HOV/T lane accessibility to the value of CAV decals.

14. Who are the early adopters of fuel cell vehicles?

Authors: Scott Hardman, Gil Tal

Publication date: 2018/9/13

Journal: International Journal of Hydrogen Energy

Volume: 43

Issue: 37

Pages: 17857-17866

Publisher: Pergamon

Description:

All modern technologies, including automotive technologies, are first purchased by early adopters. These consumers are currently posed with the choice of purchasing a fuel cell vehicle (FCV) or a variety of other alternatively fueled vehicles, including battery electric vehicles (BEVs). For FCVs to be commercially successful they need to carve out their own niche in the automotive market, something which may prove challenging in the face of strong BEV market growth. The results in this paper come from a questionnaire survey of 470 FCV owners and 1550 BEV owners. The paper explores the socio-economic profile, travel patterns, and attitudes of FCV buyers and compares them to the buyers of BEVs. The result suggests that the adopters of BEVs and FCV are similar in gender, level of education, household income, and have similar travel patterns. They have differences in age, ownership of previous alternative fuel …

15. Estimating the Longest Trip for Plug-In Electric Vehicle Households

Authors: Rosaria M Berliner, Gil Tal, Alan Jenn

Publication date: 2018

Source: Transportation Research Board 97th Annual Meeting Transportation Research Board

Issue: 18-04792

Description:

Long distance road trips are underreported and underestimated in many travel behavior studies. These infrequent trips of several hundred miles account for a non-trivial percentage of vehicle and household vehicle miles traveled (VMT), yet many studies tend to overlook, underreport, or misrepresent them. Overall, for households that own a new plug-in vehicle, a single trip (the longest in the last 12 month) accounts for 10% of the household’s annual VMT for almost 95% of households. In terms of greenhouse gas (GHG) emissions, 10% of the household's GHG emissions are accounted for by that trip for approximately 90% of households in the sample. The authors explore the variables and characteristics that effect the distance of the longest trip. They use data collected in California during June and July 2017 as part of a study that focused on plug-in electric vehicle (PEV) households. The authors estimate a log-linear model to understand the factors that influence the length of the longest road trip made in the previous 12 months. The number of household vehicles, the presence of low-range battery electric vehicles, and the number of passengers on the longest trip have the greatest impact on trip-length.